

```

#EX.NO:1.a      BasicPracticeExperiments(1to4)
#DATE : 30.07.2024

#NAME :Gokulanand b

#ROLL NO : 230701093
#DEPARTMENT : B.E COMPUTER SCIENCE AND ENGINEERING - B

import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline

data=pd.read_csv('Iris.csv')
data

```

	Id	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm
0	1	5.1	3.5	1.4	0.2
1	2	4.9	3.0	1.4	0.2
2	3	4.7	3.2	1.3	0.2
3	4	4.6	3.1	1.5	0.2
4	5	5.0	3.6	1.4	0.2
..
145	146	6.7	3.0	5.2	2.3
146	147	6.3	2.5	5.0	1.9
147	148	6.5	3.0	5.2	2.0
148	149	6.2	3.4	5.4	2.3
149	150	5.9	3.0	5.1	1.8

```

Species
' Iris-setosa'
' Iris-setosa'
' Iris-setosa'
' Iris-setosa'
' Iris-setosa'
...
' Iris-virginica'
' Iris-virginica'
' Iris-virginica'
' Iris-virginica'
' Iris-virginica'

```

[150 rows x 6 columns]

data.info()

#	Column	Non-NullCount	Dtyp
..
<class	'pandas.core.frame.DataFrame'		
RangelIndex:	150 entries, 0 to 149		
Data columns (total 6 columns):			

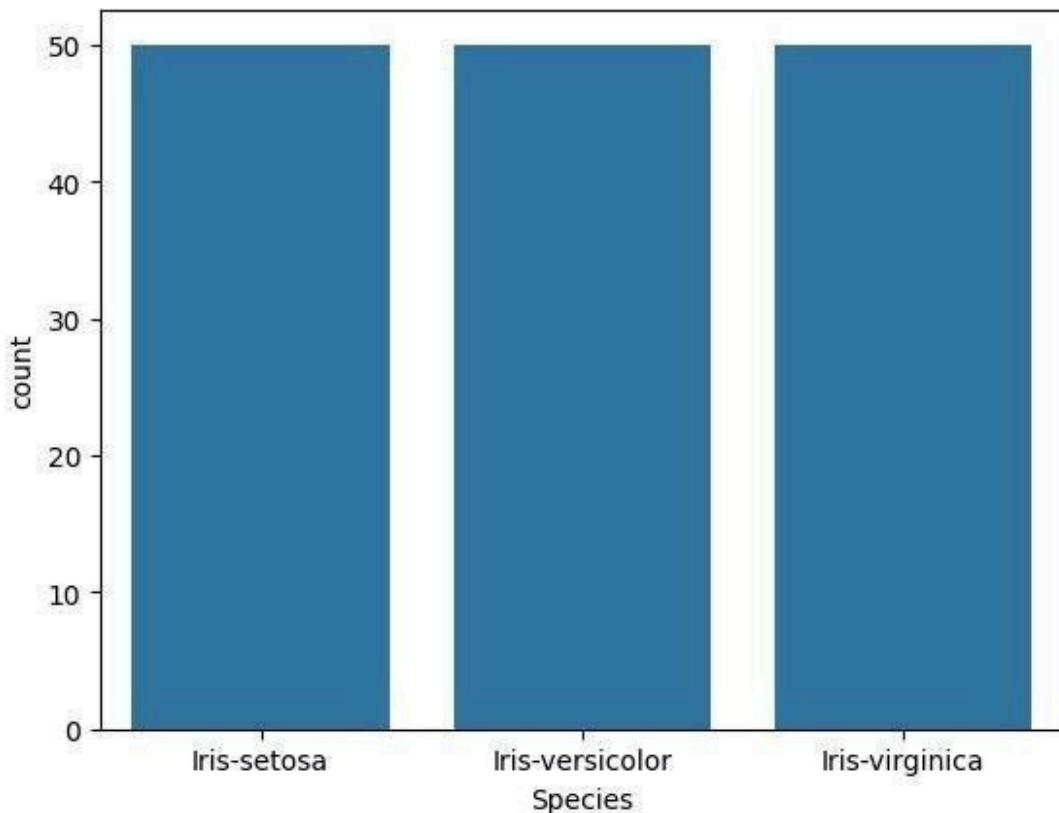
```
0   Id    150 non-null    int64
   · SepalLengthCm 150 non-null      float64
   · SepalWidthCm  150 non-null      float64
   · PetalLengthCm 150 non-null      float64
   · PetalWidthCm  150 non-null      float64
object dtypes: float64(4), int64(1),
object(1) memory usage: 7.2+ KB
data.describe()

          Id SepalLengthCm SepalWidthCm
PetalLengthCm PetalWidthCm
count 150.000000 150.000000 150.000000 150.000000
150.000000
mean 75.500000 5.843333 3.054000 3.758667
1.19866
7
std 0.76316
1
min 0.10000
0
025.3%0000
0
50% 38.25000
0
75.50000
0
1.300000
75% 112.750000
5.100000
1.800000
max 150.000000
6.900000
2.50000
0
data.value_counts('Species')

Species
```

```
Name: count, dtype: int64
```

```
sns.countplot(x='Species', data=data, )
plt.show()
```



```
dummies=pd.get_dummies(data.Species)

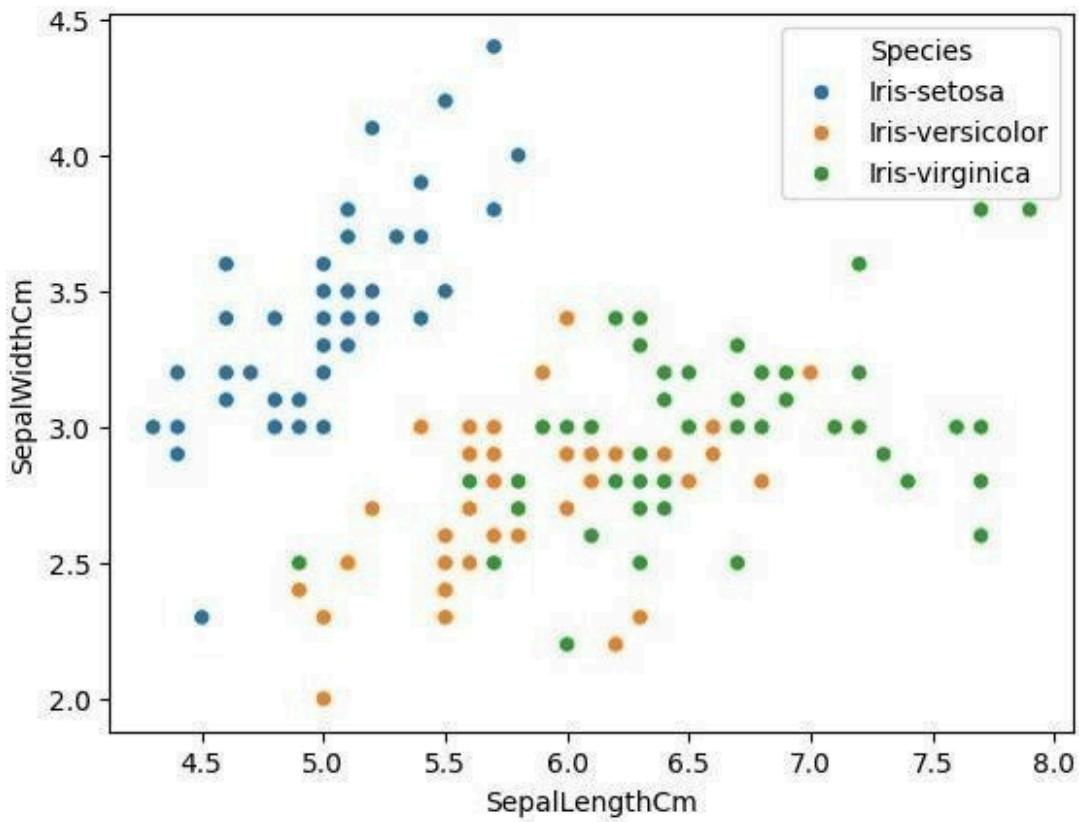
FinalDataset=pd.concat([pd.get_dummies(data.Species),data.iloc[:,[0,1,2,3]],axis=1)

FinalDataset.head()

   Iris-setosa  Iris-versicolor  Iris-virginica  Id      SepalLengthCm \
0          True        False    False  1                         m
   .          True        False    False  2                         5.1
   .          True        False    False  3                         4.9
   .          True        False    False  4                         4.7
   .          True        False    False  5                         4.6
   .          True        False    False  6                         5.0
   .          True        False    False  7
   .          True        False    False  8
   .          True        False    False  9
   .          True        False    False  10
   .          True        False    False  11
   .          True        False    False  12
   .          True        False    False  13
   .          True        False    False  14
   .          True        False    False  15
   .          True        False    False  16
   .          True        False    False  17
   .          True        False    False  18
   .          True        False    False  19
   .          True        False    False  20
   .          True        False    False  21
   .          True        False    False  22
   .          True        False    False  23
   .          True        False    False  24
   .          True        False    False  25
   .          True        False    False  26
   .          True        False    False  27
   .          True        False    False  28
   .          True        False    False  29
   .          True        False    False  30
   .          True        False    False  31
   .          True        False    False  32
   .          True        False    False  33
   .          True        False    False  34
   .          True        False    False  35
   .          True        False    False  36
   .          True        False    False  37
   .          True        False    False  38
   .          True        False    False  39
   .          True        False    False  40
   .          True        False    False  41
   .          True        False    False  42
   .          True        False    False  43
   .          True        False    False  44
   .          True        False    False  45
   .          True        False    False  46
   .          True        False    False  47
   .          True        False    False  48
   .          True        False    False  49
   .          True        False    False  50
```

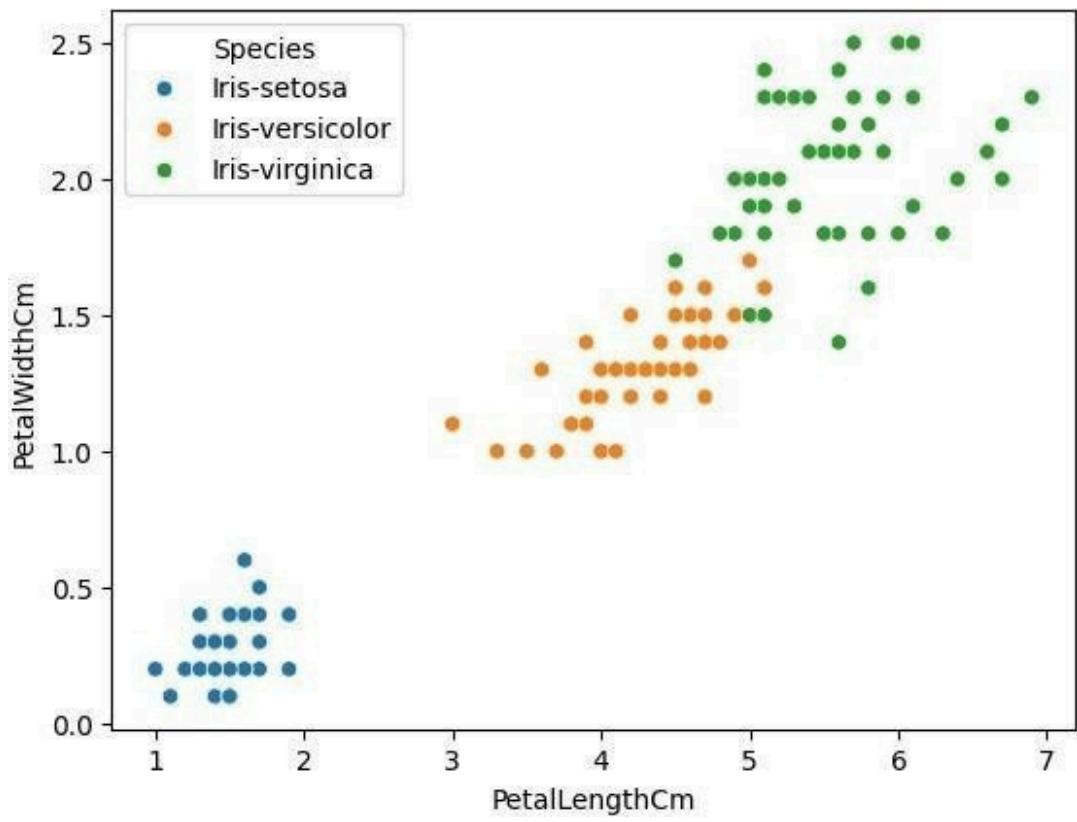
```
sns.scatterplot(x='SepalLengthCm',y='SepalWidthCm',hue='Species',data=
data,)

<Axes: xlabel='SepalLengthCm', ylabel='SepalWidthCm'>
```

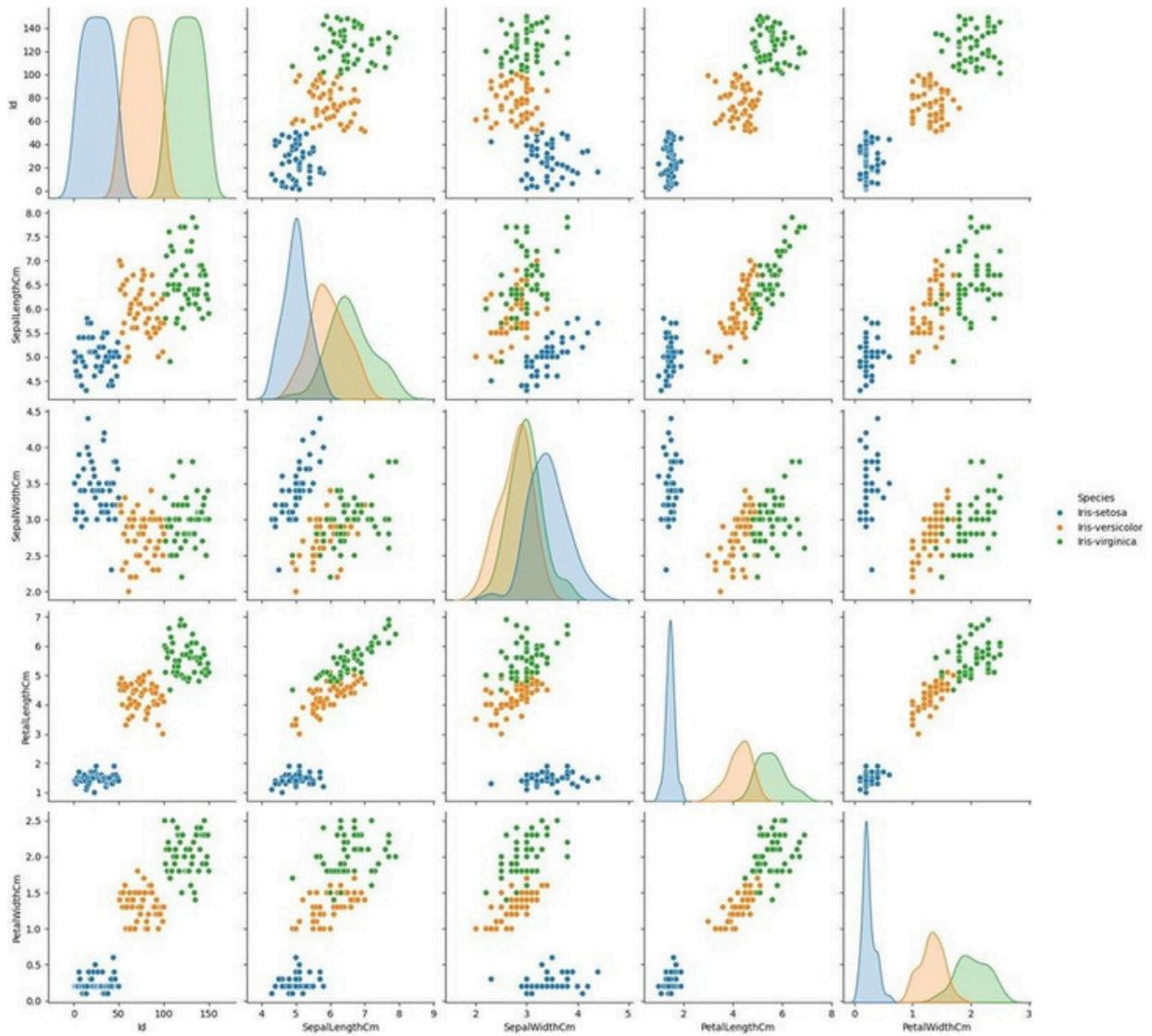


```
sns.scatterplot(x='PetalLengthCm', y='PetalWidthCm', hue='Species', data=
data,)

<Axes: xlabel='PetalLengthCm', ylabel='PetalWidthCm'>
```

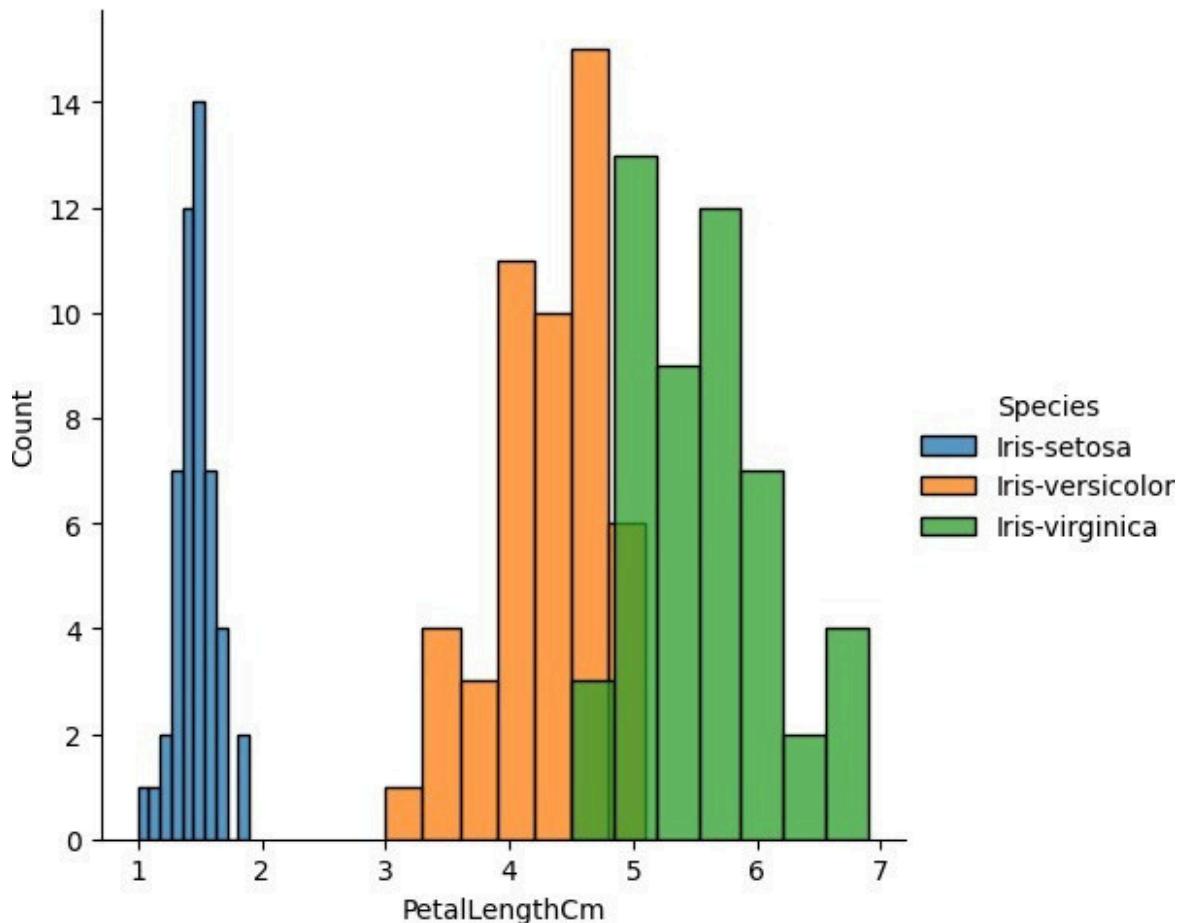


```
sns.pairplot(data,hue='Species',height=3);
```

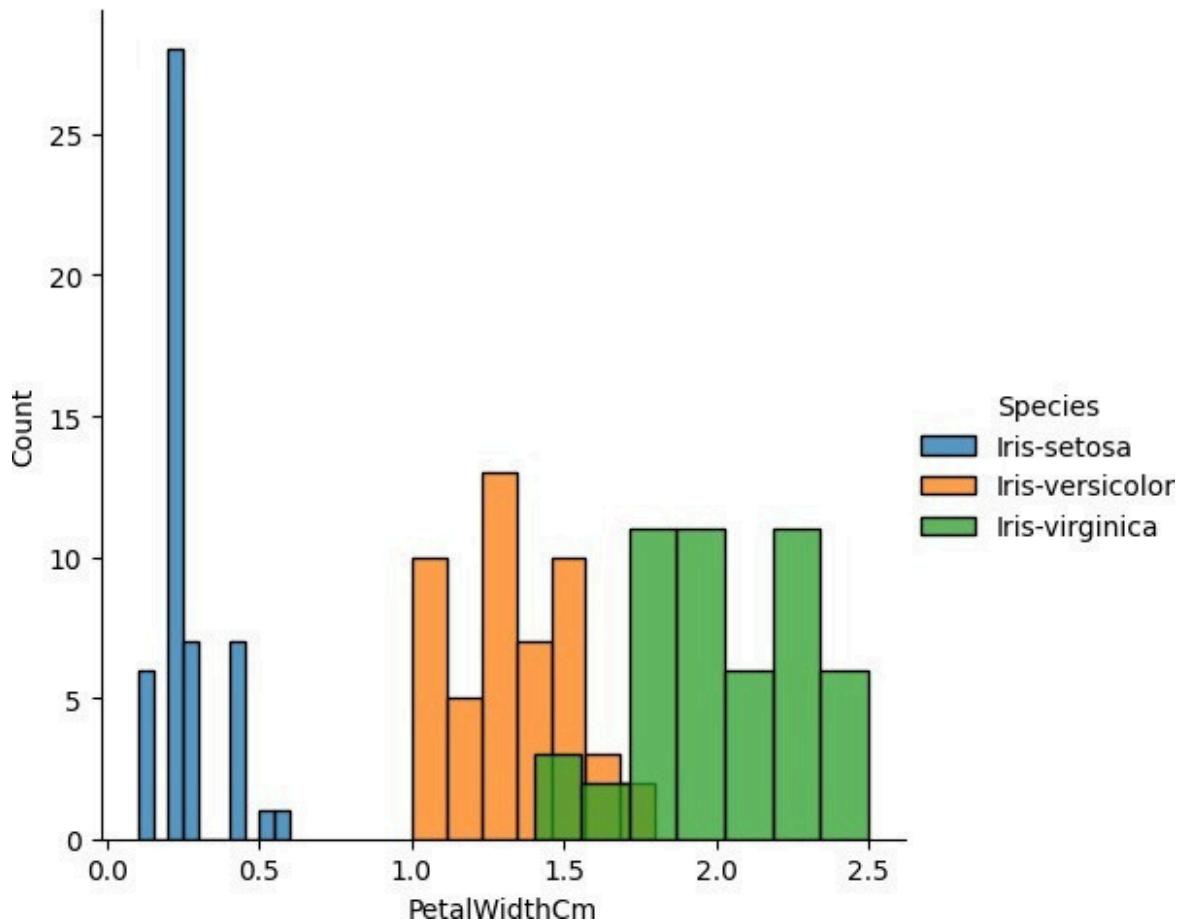


```
plt.show()

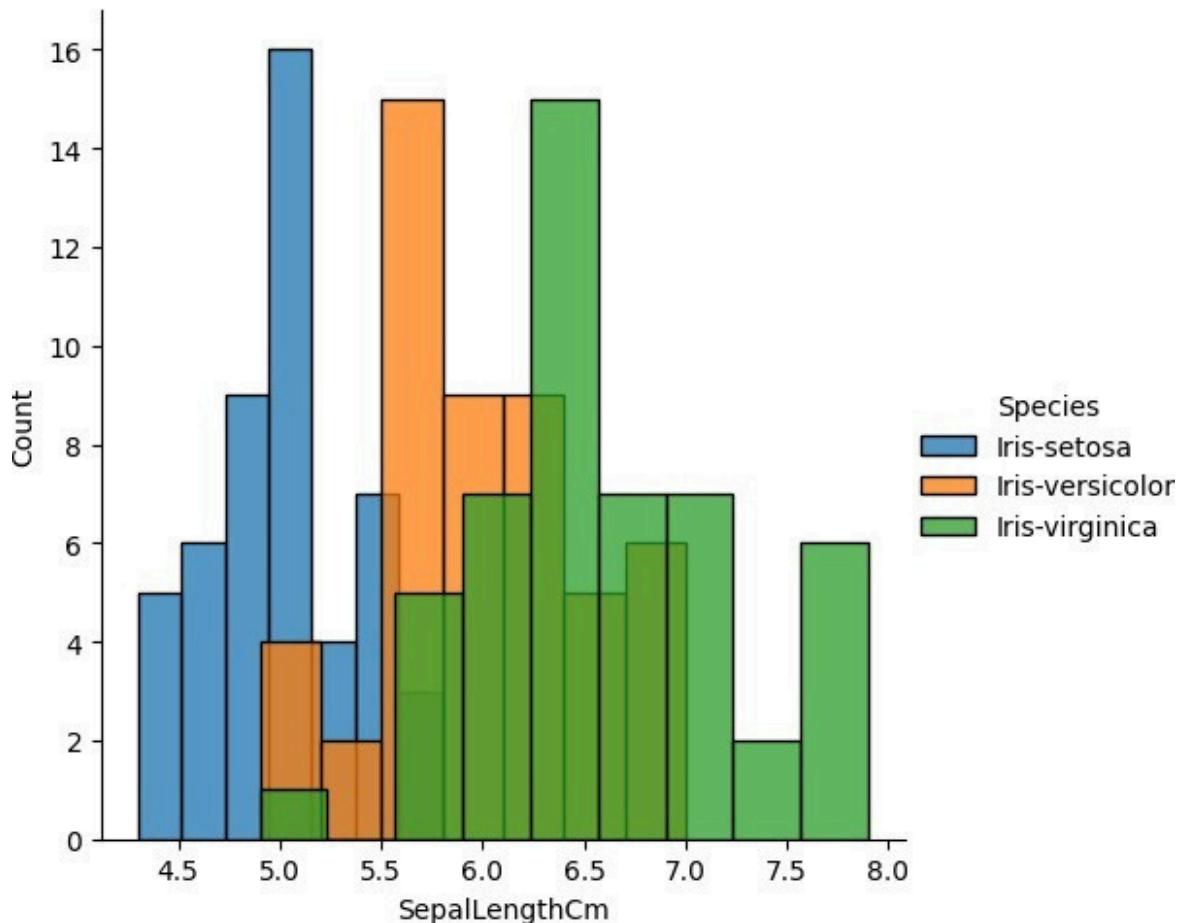
sns.FacetGrid(data,hue='Species',height=5).map(sns.histplot,'PetalLengthCm').add_legend();
plt.show();
```



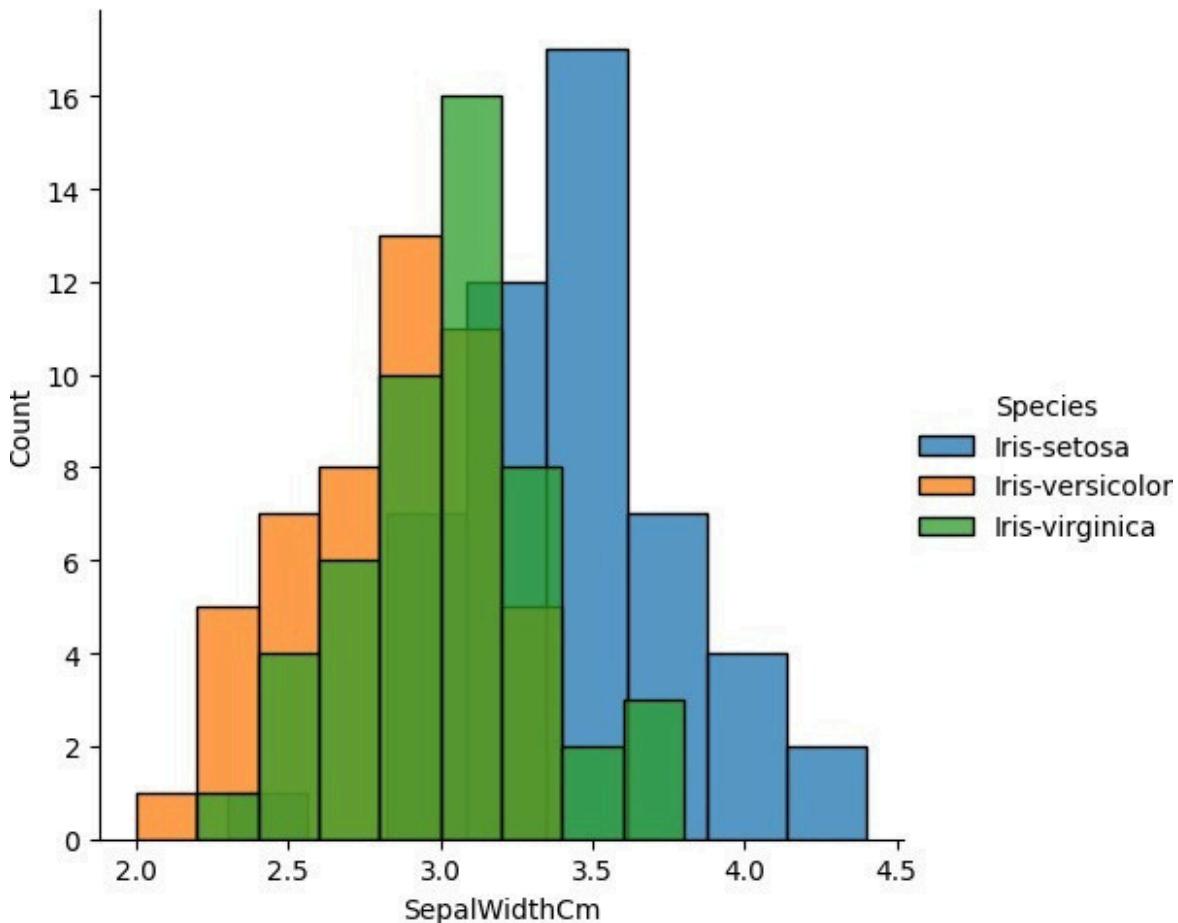
```
sns.FacetGrid(data,hue='Species',height=5).map(sns.histplot,'PetalWidthCm').add_legend();
plt.show();
```



```
sns.FacetGrid(data,hue='Species',height=5).map(sns.histplot,'SepalLengthCm').add_legend();
plt.show();
```



```
sns.FacetGrid(data,hue='Species',height=5).map(sns.histplot,'SepalWidthCm').add_legend();
plt.show();
```



```
#EX.NO :1.b Pandas Buit in function. Numpy Buit in fuction- Array
slicing, Ravel,Reshape,ndim
#DATA : 06.08.2024
#NAME :Gokulanand b
#ROLL NO :230701093
#DEPARTMENT : B.E COMPUTER SCIENCE AND ENGINEERING - B

import numpy as np
array=np.random.randint(1,100,9)
array

array([39, 97, 88, 58, 29, 87, 27, 88, 91])
np.sqrt(array)

array([6.244998 , 9.8488578 , 9.38083152, 7.61577311, 5.38516481,
 9.32737905, 5.19615242, 9.38083152, 9.53939201])

array.ndim
```

```

1
new_array=array.reshape(3,3)
new_array

array([[39, 97,
       88],
       [58, 29, 87],
       [27, 88, 91]])

new_array.ndim
2

new_array.ravel()
array([39, 97, 88, 58, 29, 87, 27, 88, 91])

newm=new_array.reshape(3,3)
newm

array([[39, 97,
       88],
       [58, 29, 87],
       [27, 88, 91]])

newm[2,1:3]
array([88, 91])

newm[1:2,1:3]
array([[29, 87]])

new_array[0:3,0:0]
array([], shape=(3, 0), dtype=int32)

new_array[1:3]

array([[58, 29, 87],
       [27, 88, 91]])

#EX.NO :2 Outlier detection #DATA : 13.08.2024
#NAME : GOKULANAND B
#ROLL NO : 230701093
#DEPARTMENT : B.E COMPUTER SCIENCE AND
ENGINEERING - B

import numpy as np
import warnings
warnings.filterwarnings('ignore')

```

```
array=np.random.randint(1,100,16)
array

array([37, 15, 49, 89, 30, 47, 2, 86, 53, 63, 41, 46, 42, 27, 5,
97])

array.mean()

45.5625

np.percentile(array,25)

29.25

np.percentile(array,50)

44.0

np.percentile(array,75)

55.5

np.percentile(array,100)

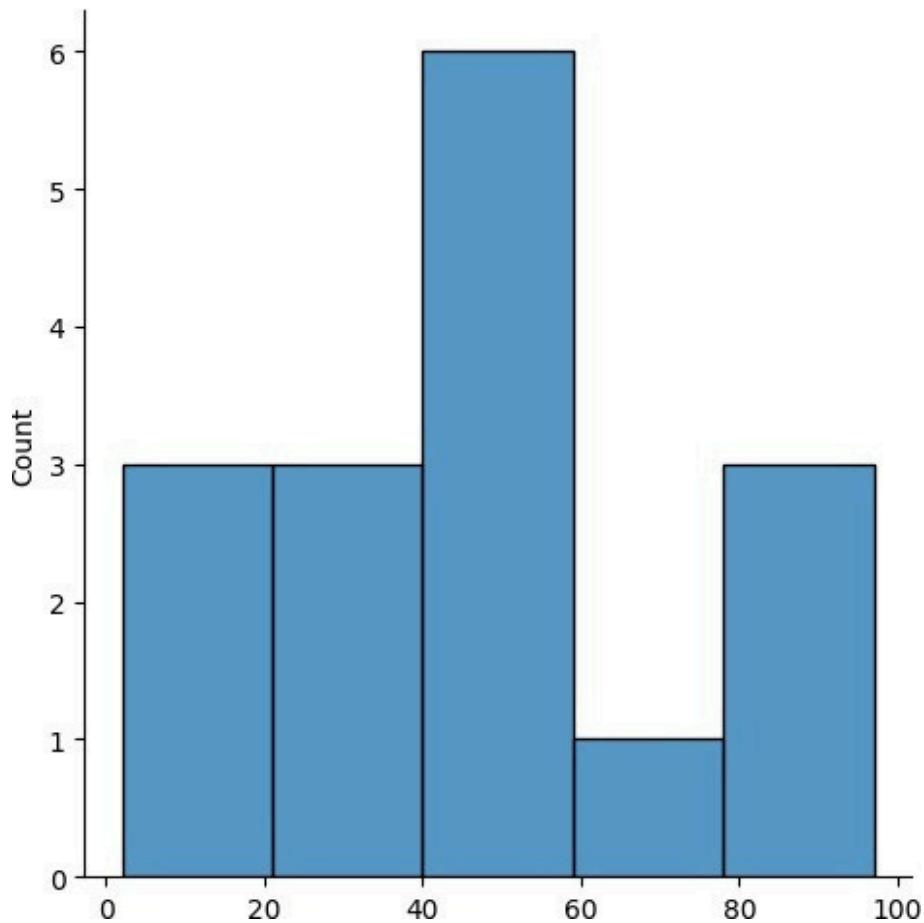
97.0

#outliers detection
def outDetection(array):
    sorted(array)
Q1,Q3=np.percentile(array,[25,75])
IQR=Q3-Q1
lr=Q1-(1.5*IQR)
    ur=Q3+(1.5*IQR)
    return lr,ur
lr,ur=outDetection(array)
lr,ur

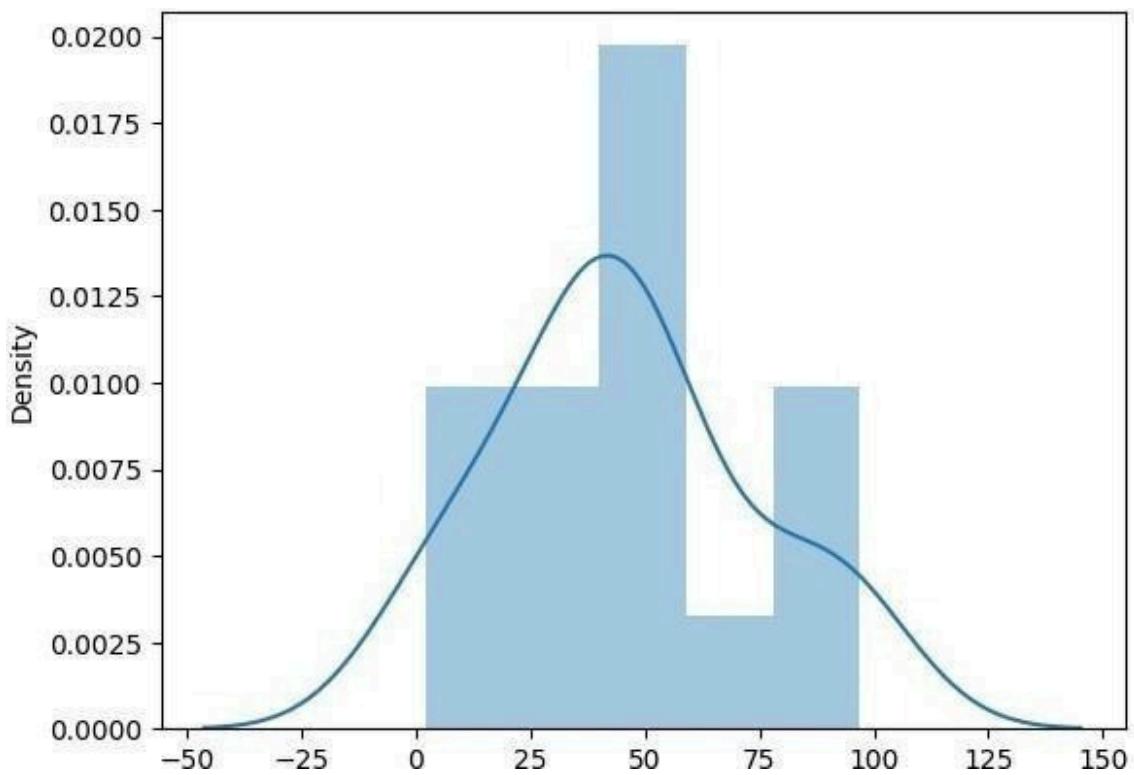
(-10.125, 94.875)

import seaborn as sns
%matplotlib inline
sns.displot(array)

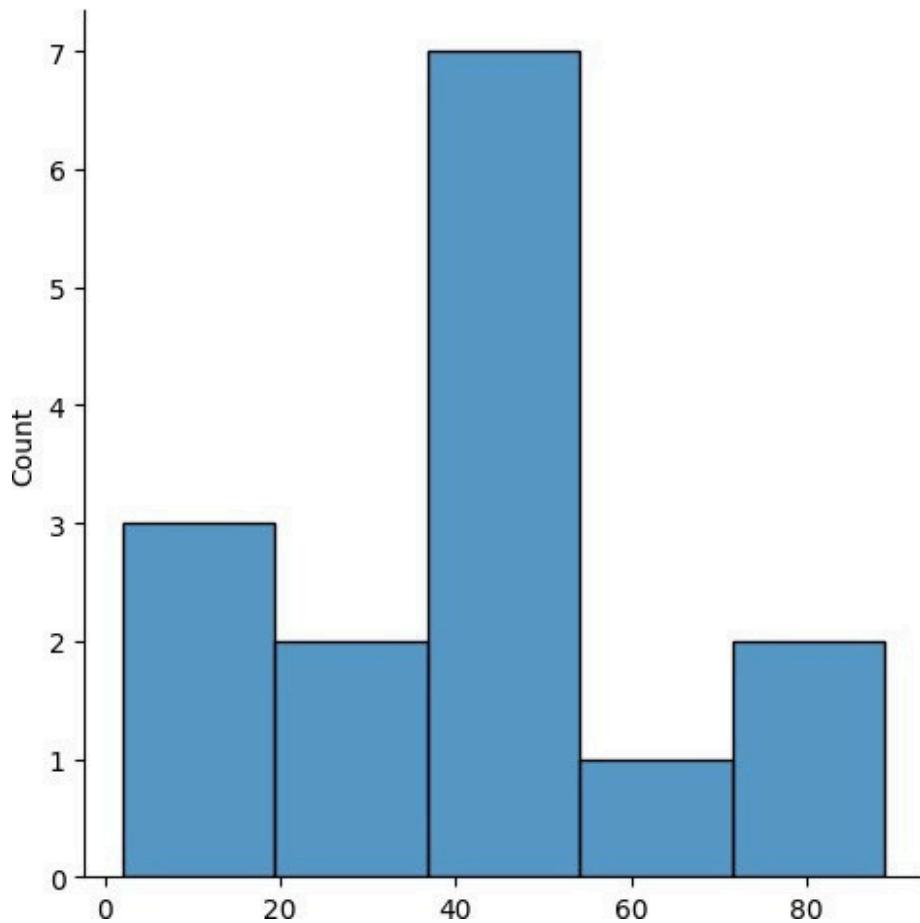
<seaborn.axisgrid.FacetGrid at 0x20d7cda3b50>
```



```
sns.distplot(array)  
<Axes: ylabel='Density'>
```



```
new_array=array[ (array>lr) & (array<ur) ]
new_array
array([37, 15, 49, 89, 30, 47, 2, 86, 53, 63, 41, 46, 42, 27, 5])
sns.displot(new_array)
<seaborn.axisgrid.FacetGrid at 0x20d7d02d950>
```

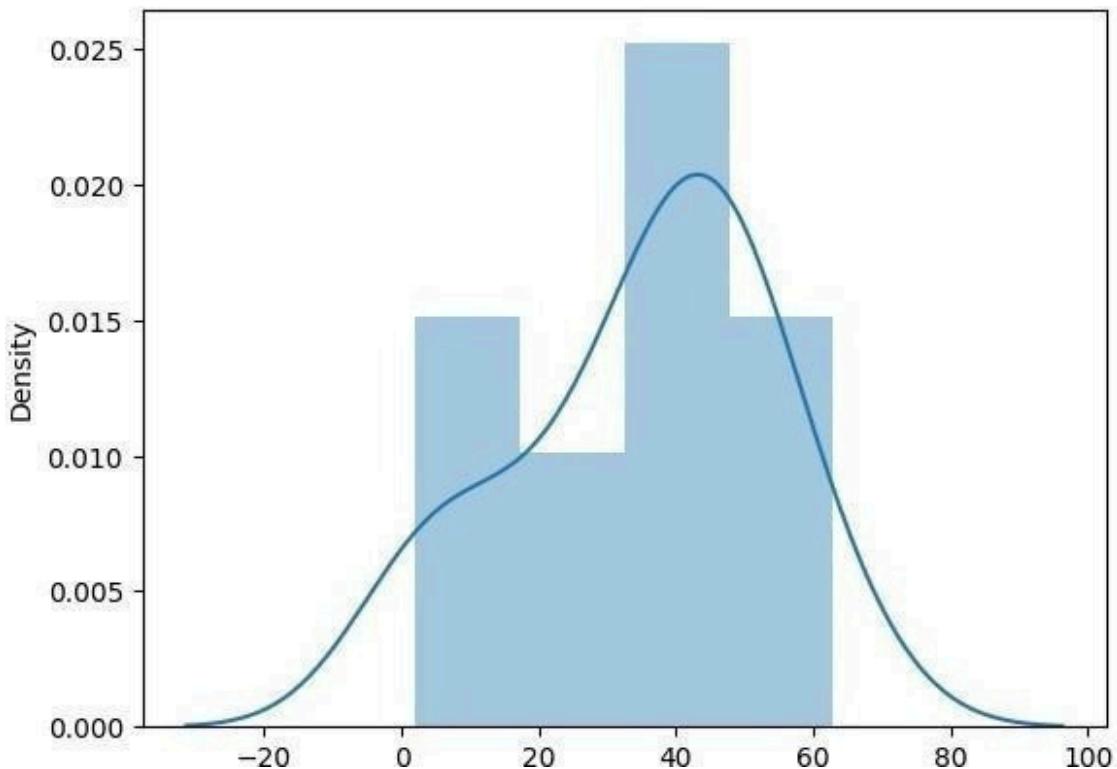


```
lr1,url=outDetection(new_array)
lr1,url
(-5.25, 84.75)

final_array=new_array[ (new_array>lr1) & (new_array<url)]
final_array

array([37, 15, 49, 30, 47, 2, 53, 63, 41, 46, 42, 27, 5])
sns.distplot(final_array)

<Axes: xlabel='Density'>
```



```
#EX.NO :3 Missing and inappropriate data
#DATA : 20.08.2024
```

#NAME: GOKULANAND B
#ROLL NO: 230701093
#DEPARTMENT: B.E COMPUTER SCIENCE AND ENGINEERING - B

```
import numpy as np
import pandas as pd
import warnings
warnings.filterwarnings('ignore')
df=pd.read_csv("Hotel_Dataset.csv")
df
```

	CustomerID	Age_GroupRating(1-5)		Hotel	FoodPreference	Bill
0	1	20-25	4	Ibis	veg	1300
1	2	30-35	5	LemonTree	Non-Veg	2000
2	3	25-30	6	RedFox	Veg	1322
3	4	20-25	-1	LemonTree	Veg	1234

4	5	35+	3	Ibis	Vegetarian	989
5	6	35+	3	Ibys	Non-Veg	1909
6	7	35+	4	RedFox	Vegetarian	1000
7	8	20-25	7	LemonTree	Veg	2999
8	9	25-30	2	Ibis	Non-Veg	3456
9	9	25-30	2	Ibis	Non-Veg	3456
10	10	30-35	5	RedFox	non-Veg	-6755

```
NoOfPax EstimatedSalaryAge_Group.1
0 1      2      40000    20-25
2 3      3      59000    30-35
4 5      2      30000    25-30
6 7      2      120000   20-25
8 9      2      45000    35+
10       2      122220   35+
      -1      21122   35+
      -10     345673   20-25
      3      -99999   25-30
      3      -99999   25-30
      4      87777    30-35
```

```
5      e
df.duplicated()
7      e
8      False
9      e
dtype: bool
10     e
      False
      e
      False
      e
      False
      e
      True
      False
```

```
df.info()                                     <class  
'pandas.core.frame.DataFrame'>  
RangeIndex: 11 entries, 0 to 10  
Data columns (total 9 columns):  
 #   Column           Non-NullCount   Dtype    
---  --  
 0   CustomerID      11 non-null     int64  
 1   Age_Group       11 non-null     object  
 2   Rating(1-5)     11 non-null     int64
```

```

      · Hotel      11 non-null          objec
      : FoodPreference 11 non-null       t
      : Bill        11 non-null         éBjéc
      · NoOfPax    11 non-null         t
      · Age_Group1 11 non-null         int6
      · EstimatedSalary 11 non-null     4
object dtypes: int64(5), object(4)
memory usage: 924.0+ bytes           int6
                                         4
                                         4
df.drop_duplicates(inplace=True)
) df

   CustomerID Age_Group Rating(1-5)      Hotel FoodPreference Bill
\ 0          1    20-25             4      Ibis      veg  1300
  1          2    30-35             5  LemonTree  Non-Veg2000
  2          3    25-30             6      RedFox      Veg  1322
  3          4    20-25            -1  LemonTree      Veg1234
  4          5      35              3      Ibis  Vegetarian   989
  5          6      +              3      Ibis  Non-Veg1909
  6          7    35+              4      RedFox  Vegetarian  1000
  7          8  20+-25             7  LemonTree      Veg2999
  8          9    25-30             2      Ibis  Non-Veg3456
  10         10   30-35             5      RedFox  non-Veg-6755

   NoOfPax  EstimatedSalary Age_Group1
0      1        40000    20-25
2      3        59000    30-35
4      5        30000    25-30
6      7       120000    20-25
8      0        45000    35+
1      2       122220    35+
len(df) -10       21122    35+
10     3       345673    20-25
               3        -99999   25-30
                   4        87777   30-35

```

```

index=np.array(list(range(0,len(df))))
df.set_index(index,inplace=True)
index
array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9])
df

   CustomerID Age_Group Rating(1-5) Hotel FoodPreference Bill
NoOfPax \
0           1    20-25          4     Ibis      veg 1300
2
31          2    30-35          5 LemonTree Non-Veg 2000
2
2           3    25-30          6 RedFox      Veg 1322
23          4    20-25         -1 LemonTree      Veg 1234
2
6           5    35+            3     Ibis Vegetarian 989
-1          6    35+            3     Ibis Vegetarian 989
7           7    35+            4     Ibis Non-Veg 1909
-10         8    20-25          7 RedFox Vegetarian 1000
8
3           9    25-30          2     Ibis Non-Veg 3456
4
10          10   30-35          5 RedFox non-Veg-6755

   EstimatedSalary Age_Group1
y
0 1 2 3        40000    20-25
4           59000    30-35
5           30000    25-30
6           120000   20-25
7           45000    35+
8           122220   35+
9           21122    35+
10          345673   20-25
df.drop(['Age_Group1'],axis=1,inplace=True)
99999
25-30
87777
30-35

```

) df

	1	20-25	4	Ibis	veg	1300
0						0

2

Rating(1-5)
NoOfPax \

CustomerID Age_Group
Hotel FoodPreference Bill

3	2	30-35	5	LemonTree	Non-Veg	2000
2	2		6	RedFox	Veg	1322
3	2	25-30	-1	LemonTree	Veg	1234
4	2	20-25	3	Ibis	Vegetarian	989
5	2	35	3	Ibys	Non-Veg	1909
6	-1	+	4	RedFox	Vegetarian	1000
7	5	35	7	LemonTree	Veg	2999
8	3	20+25	2	Ibis	Non-Veg	3456
9	4	25350	5	RedFox	non-Veg	-6755
<hr/>						
EstimatedSalary						
0	40000					
1	59000					
2	30000					
3	120000					
4	45000					
5	122220					
6	21122					
7	345673					
8	-99999					
9	87777					
 df.CustomerID.loc[df.CustomerID<0]=np.nan df.Bill.loc[df.Bill<0]=np.nan df.EstimatedSalary.loc[df.EstimatedSalary<0]=np.nan ndf						
CustomerIDAge_GroupRating(1-5) HotelFoodPreference Bill						
0	1.0	20-25	4	Ibis	veg	1300.0
1	2.0	30-35	5	LemonTree	Non-Veg	2000.
2	3.0	25-30	6	RedFox	Veg	0
3	4.0	20-25	-1	LemonTree	Veg	1232342..0

4	5.0	35	3	Ibis	Vegetarian	989.0
5	6.	+	3	Ibys	Non-Veg	1909.0
	0	35				
6	7.0	35+	4	RedFox	Vegetarian	1000.0
7	8.0	20-25	7	LemonTree	Veg	2999.0
8	9.0	25-30	2	Ibis	Non-Veg	3456.0
9	10.0	30-35	5	RedFox	non-Veg	NaN

NoOfPax EstimatedSalary

0	2	40000.0
1	3	59000.0
2	2	30000.0
3	2	120000.0
4	2	45000.0
5	2	122220.0
6	-1	21122.0
7	-10	345673.0
8	3	NaN
9	4	87777.0

```
df['NoOfPax'].loc[(df['NoOfPax']<1) | (df['NoOfPax']>20)]=np.nan
```

df

	CustomerID	Age_Group	Rating(1-5)	Hotel	FoodPreference	Bill
0	1.0	20-25	4	Ibis	veg	1300.0
1	2.0	30-35	5	LemonTree	Non-Veg	2000.0
2	3.0	25-30	6	RedFox	Veg	1322.0
3	4.0	20-25	-1	LemonTree	Veg	1234.0
4	5.0	35+	3	Ibis	Vegetarian	989.0
5	6.0	35+	3	Ibys	Non-Veg	1909.0
6	7.0	35+	4	RedFox	Vegetarian	1000.0
7	8.0	20-25	7	LemonTree	Veg	2999.0
8	9.0	25-30	2	Ibis	Non-Veg	3456.0

```

9      10.0    30-35      5     RedFox    non-Veg    NaN
      NoOfPax EstimatedSalary
0        2.0        40000.0
1        3.0        59000.0
2        2.0        30000.0

3        2.0       120000.0
4        2.0        45000.0
5        2.0       122220.0
6        NaN        21122.0
7        NaN       345673.0
8        3.0        NaN
9        4.0       87777.0

df.Age_Group.unique()
array(['20-25', '30-35', '25-30', '35+'], dtype=object)
df.Hotel.unique()
array(['Ibis', 'LemonTree', 'RedFox', 'Ibys'], dtype=object)
df.Hotel.replace(['Ibys'], 'Ibis', inplace=True)
df.FoodPreference.unique
<boundmethod Series.unique of0          veg
9
g
Non-Ve
g
non-Ve
g

Name: FoodPreference,           dtype: object>
df.FoodPreference.replace(['Vegetarian', 'veg'], 'Veg', inplace=True)
df.FoodPreference.replace(['non-Veg'], 'Non-Veg', inplace=True)
df.EstimatedSalary.fillna(round(df.EstimatedSalary.mean()), inplace=True)
df.NoOfPax.fillna(round(df.NoOfPax.median()), inplace=True)
df['Rating(1-5)'].fillna(round(df['Rating(1-5)'].median()), inplace=True)
df.Bill.fillna(round(df.Bill.mean()), inplace=True)
df

```

	CustomerID	Age_Group	Rating(1-5)	Hotel	FoodPreference	Bill
0	1.0	20-25	4	Ibis	Veg	1300.0
1	2.0	30-35	5	LemonTree	Non-Veg	2000.0
2	3.0	25-30	6	RedFox	Veg	1322.0
3	4.0	20-25	-1	LemonTree	Veg	1234.0

4	5.0	35	3	Ibi	Veg	989.0
5	6.0	+ 35+	3	s	Non-Veg	1909.0
6	7.0	20+-2	4	RedFox	Veg	1000.0
7	8.	5	7	LemonTree	Veg	2999.0
8	9.0	25-30	2	Ibis	Non-Veg	3456.0
9	10.0	30-35	5	RedFox	Non-Veg	1801.0

	NoOfPax	EstimatedSalary
0	2.0	40000.0
1	3.0	59000.0
2	2.0	30000.0
3	2.0	120000.0
4	2.0	45000.0
5	2.0	122220.0
6	2.0	21122.0
7	2.0	345673.0
8	3.0	96755.0
9	4.0	87777.0

#EX.NO :4 Data Preprocessing

#DATA : 27.08.2024

#NAME : GOKULANAND B

#ROLL NO : 230701093

#DEPARTMENT : B.E COMPUTER SCIENCE AND

ENGINEERING - B

```
import numpy as np
import pandas as pd
import warnings
warnings.filterwarnings('ignore')
d.read_csv("pre_process_datasample.csv")
```

	Country	Age	Salary	Gender	Marital Status
0	USA	44.	72000	Male	Yes
1	France	30	48000.0	Female	No
2	Spain	27.0	54000.0	Male	Yes
3	Germany	30.0	61000.0	Female	No
4	USA	38.0	NaN	Male	No
5	Spain	40.0	58000	Male	No

```

df.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10 entries, 0 to 9
Data columns (total 4 columns):
 #   Column      Non-NullCount Dtyp
 ----  --          --           --
 0   Country     10 non-null    object
 1   Age         9 non-null    float64
 2   Salary       9 non-null    float64
 3   Purchased   10 non-null    float64
object dtypes: float64(2), object(2)
memory usage: 452.0+ bytes

df.Country.mode()

0    France
Name: Country, dtype:
object df.Country.mode()[0]
'France'

type(df.Country.mode())
pandas.core.series.Series

df.Country.fillna(df.Country.mode()[0], inplace=True)
df.Age.fillna(df.Age.median(), inplace=True)
df.Salary.fillna(round(df.Salary.mean()), inplace=True)

) df
   Countr    Age    Salary
0      y  44.  70000based    N
1  France  0    48000.0      o
2  Spain  27.0  54000.0      Ye
3  German 30.0  61000.0      s
4      y  38.0  63778.0      No
5  Spain  40.0  58000.0      No
6  German 35.0  52000.0      Ye
7      y  38.0  79000.0      s
8  France 48.0  83000.0      Ye
9  Spain  50.0  67000.0      s
pd.get_dummies(df.Country)
   France  Germany  Spain
  True      False  False    s
  False      False  True    No
  False      True  False    Ye
  False      False  True    s
  False      True  False    Ye

```

```

5      True  False  False
6     False  False   True
7     True  False  False
8    False       True False
9     True  False  False

```

```

updated_dataset=pd.concat([pd.get_dummies(df.Country),df.iloc[:,[1,2,3]]],axis=1)
df.info()

```

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10 entries, 0 to 9
Data columns (total 4 columns):

#	Column	Non-NullCount	Dtyp
0	Country	10 non-null	object
1	Age	10 non-null	float64
2	Salary	10 non-null	float64
3	Purchased	10 non-null	object

dtypes: float64(2), object(2)
memory usage: 452.0+ bytes

```
updated_dataset.Purchased.replace(['No','Yes'],[0,1],inplace=True)
```

#EX.NO :5 EDA-Quantitative and Qualitative plots
#DATA : 27.08.2024
#NAME : GOKULANAND B
#ROLL NO : 230701093
#DEPARTMENT : B.E COMPUTER SCIENCE AND ENGINEERING - B

```

import numpy as np
import pandas as pd
import warnings
warnings.filterwarnings('ignore')
df=pd.read_csv("pre_process_datasample.csv")

```

```
) df
```

	Country	Age	Salary	Purchased
0	y	44.	72000	No
1	France	0	48000.0	o
2	Spain	27.0	54000.0	Ye
3	German	30.0	61000.0	s
4	y	38.0	NaN	No
5	Spain	40.0	58000.	No
6	German	35.0	0	Ye
7	y	NaN	52000.0	s
8	France	48.	79000.0	Ye

```

df.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10 entries, 0 to 9
Data columns (total 4 columns):
 #   Column      Non-NullCount Dtyp
 ----  --          --          --
 0   Country     10 non-null    object
 1   Age         9 non-null    float64
 2   Salary       9 non-null    float64
 3   Purchased   10 non-null    float64
object dtypes: float64(2), object(2)
memory usage: 452.0+ bytes

df.Country.mode()

0    France
Name: Country, dtype:
object df.Country.mode()[0]
'France'

type(df.Country.mode())
pandas.core.series.Series

df.Country.fillna(df.Country.mode()[0], inplace=True)
df.Age.fillna(df.Age.median(), inplace=True)
df.Salary.fillna(round(df.Salary.mean()), inplace=True)

) df
   Countr    Age    Salary
0      y  44.  70000based    N
1  France  0    48000.0      o
2  Spain  27.0  54000.0      Ye
3  German 30.0  61000.0      s
4      y  38.0  63778.0      No
5  Spain  40.0  58000.0      No
6  German 35.0  52000.0      Ye
7      y  38.0  79000.0      s
8  France 48.0  83000.0      Ye
9  Spain  50.0  67000.0      s
pd.get_dummies(df.Country)
   France  Germany  Spain
  True      False  False    s
  False      False  True    No
  False      True  False    Ye
  False      False  True    s
  False      True  False    Ye

```

```
5      True  False  False
6    False  False   True
7    True  False  False
8   False       True False
9    True  False  False
```

```
updated_dataset=pd.concat([pd.get_dummies(df.Country),df.iloc[:,[1,2,3]]],axis=1)
updated_dataset
```

```
   France Germany Spain    Age   Salary
0     True  False  False  44.  72000hased    N
1    False        False   0  48000.0      o
2   True  False        27.0  54000.0      Ye
3     True  False  False  30.0  61000.0      s
4           False  True   38.0  63778.0      No
5    False        40.0  58000.0      No
6   True  False  TrueFalse  35.0  52000.0      Ye
7   False  False        38.0  79000.0      s
8   False       True  True   48.0  83000.0      Ye
9   False  False  False   50.0  67000.0      s
df.info()
RangeIndex: 10 entries, 0 to 9
Data columns (total 4 columns):
 #   Column    Non-NullCount Dtyp
 ----  -----  -----  -----
 0   Country    10 non-null    object
 1   Age         10 non-null    float64
 2   Salary       10 non-null    float64
 3   Purchased10 non-null    object
dtypes: float64(2), object(2)
memory usage: 452.0+ bytes
```

```
updated_dataset
```

```
   France Germany Spain    Age   Salary
0     True  False  False  44.  72000hased    N
1    False        False   0  48000.0      o
2   True  False        27.0  54000.0      Ye
3     True  False  False  30.0  61000.0      s
4           False  True   38.0  63778.0      No
5    False        40.0  58000.0      No
6   True  False  TrueFalse  35.0  52000.0      Ye
7   False  False        38.0  79000.0      s
8   False       True  True   48.0  83000.0      Ye
```

```

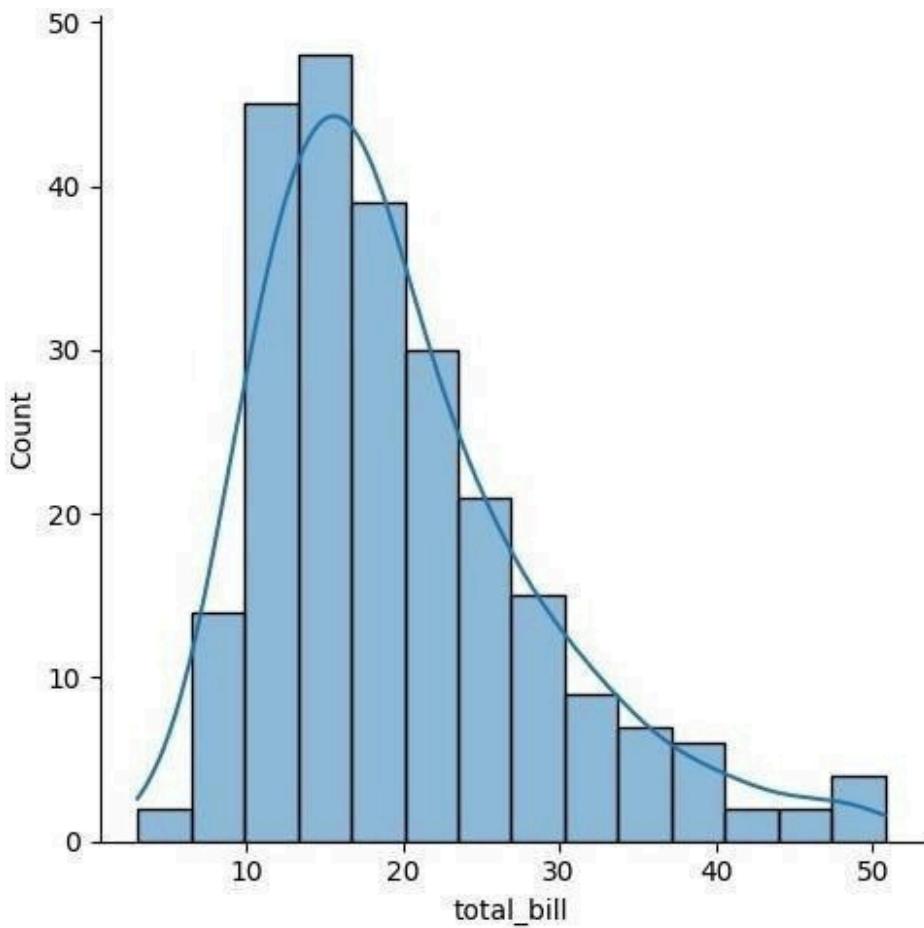
#EX.NO :5 EDA-Quantitative and Qualitative plots
#DATA : 03.09.2024

#NAME : GOKULAKRISHNAN.K
#ROLL NO : 230701094
#DEPARTMENT : B.E COMPUTER SCIENCE AND ENGINEERING - B

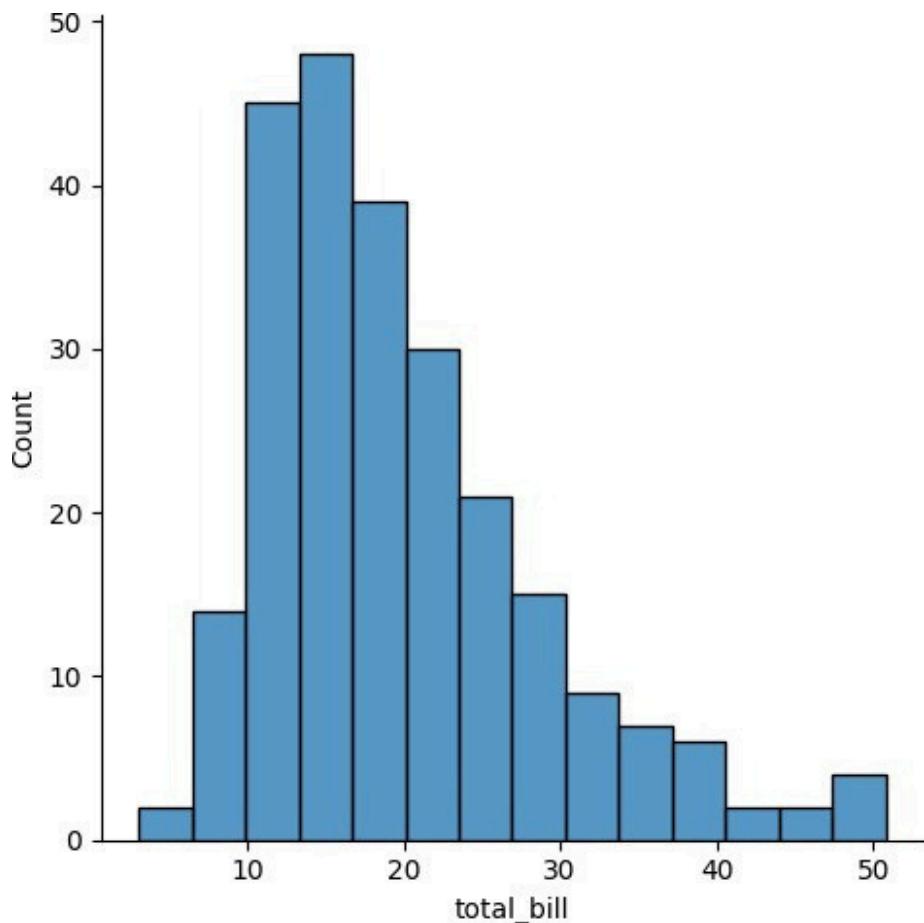
import seaborn as sns
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline

tips=sns.load_dataset('tips')
tips.head()
   total_bill      tip     sex   day   time  size
1       16.99    1.00 Female Dinner Sun   2
0       16.99    1.00   Male Dinner Sun   3
1       10.34    1.66   Male Dinner Sun   3
2       21.01    3.50 Female Dinner Sun   2
3       23.68    3.31  Male Dinner Sun   4
4       24.59    3.61  Male Dinner Sun   3
   Female N
sns.displot(tips.total_bill,kde=True)
<seaborn.axisgrid.FacetGrid at 0x20d7dc69390>

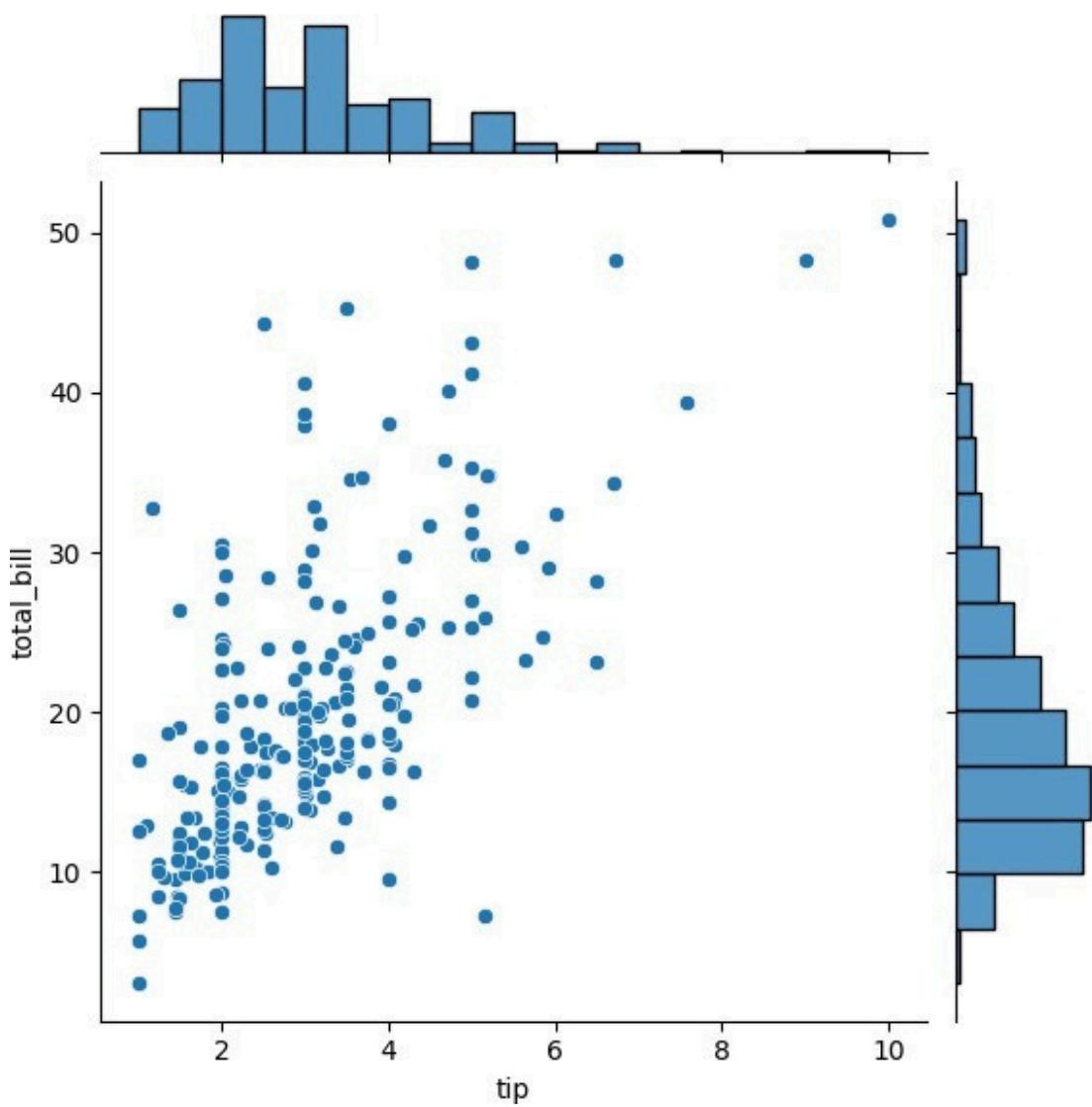
```



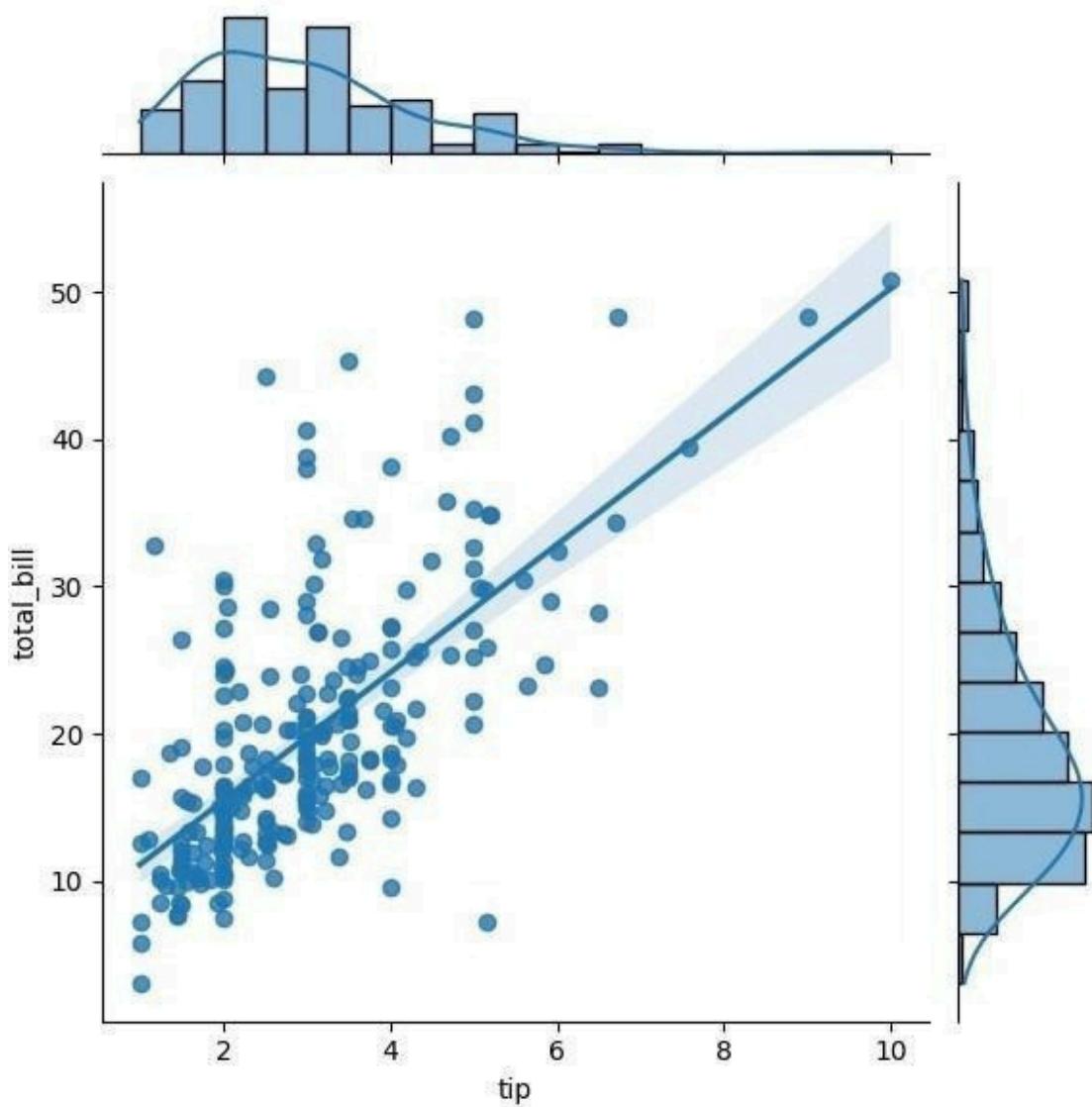
```
sns.displot(tips.total_bill, kde=False)  
<seaborn.axisgrid.FacetGrid at 0x20d7dc22790>
```



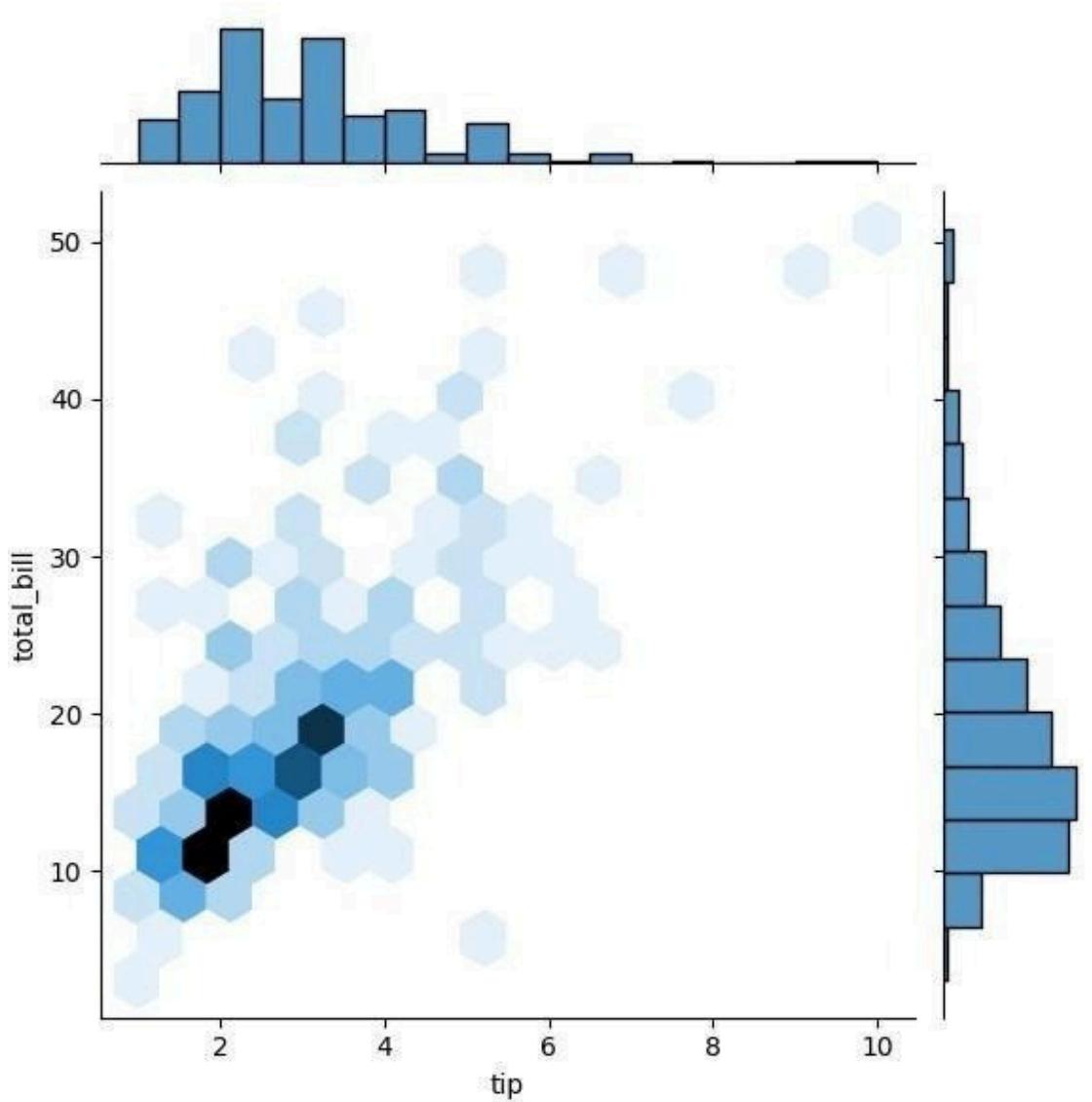
```
sns.jointplot(x=tips.tip,y=tips.total_bill)
<seaborn.axisgrid.JointGrid at 0x20d7dc2f2d0>
```



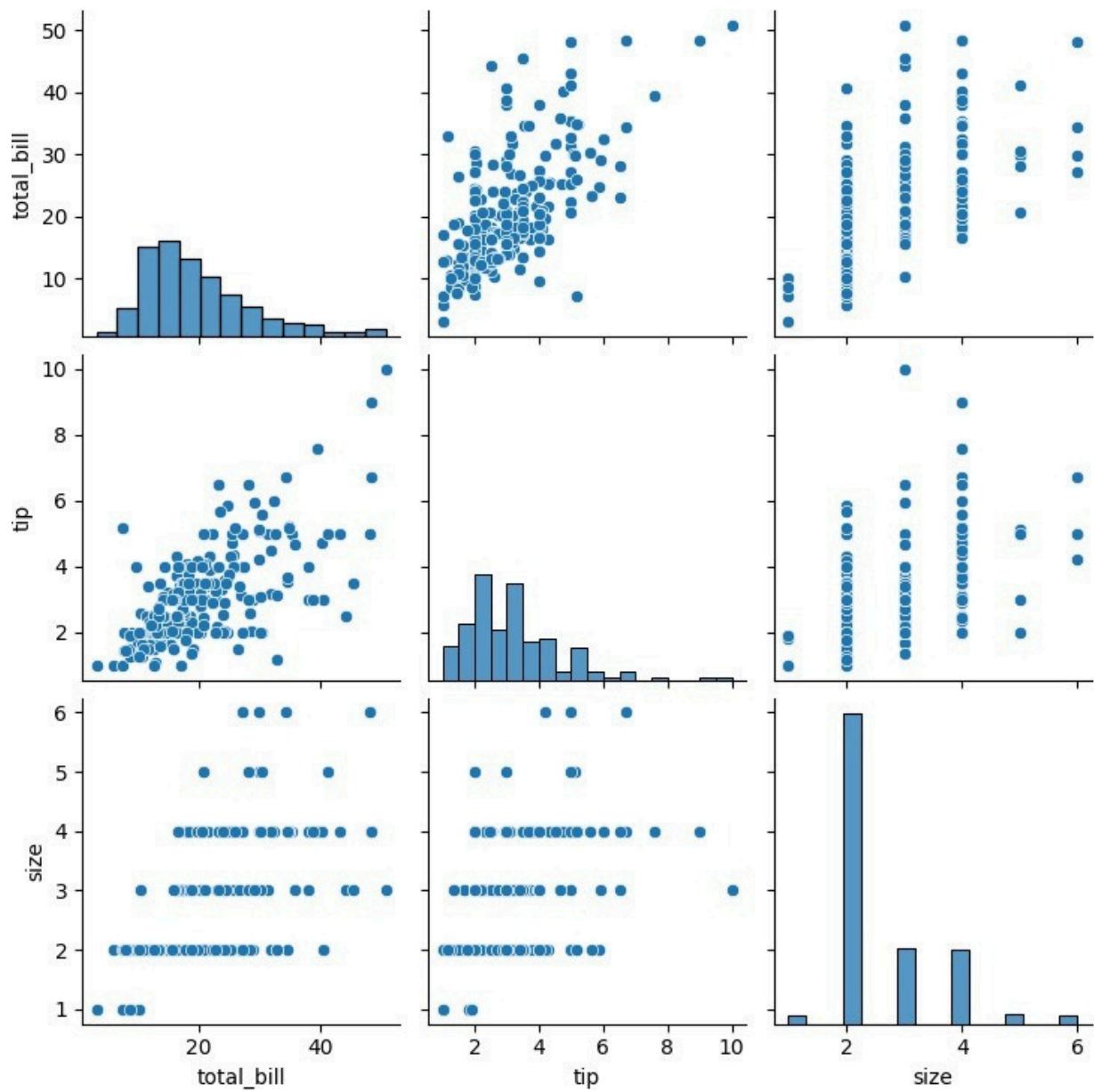
```
sns.jointplot(x=tips.tip, y=tips.total_bill, kind="reg")
<seaborn.axisgrid.JointGrid at 0x20d7ed32450>
```



```
sns.jointplot(x=tips.tip,y=tips.total_bill,kind="hex")
<seaborn.axisgrid.JointGrid at 0x20d7ed7d350>
```



```
sns.pairplot(tips)
<seaborn.axisgrid.PairGrid at 0x20d7f1c9cd0>
```



```

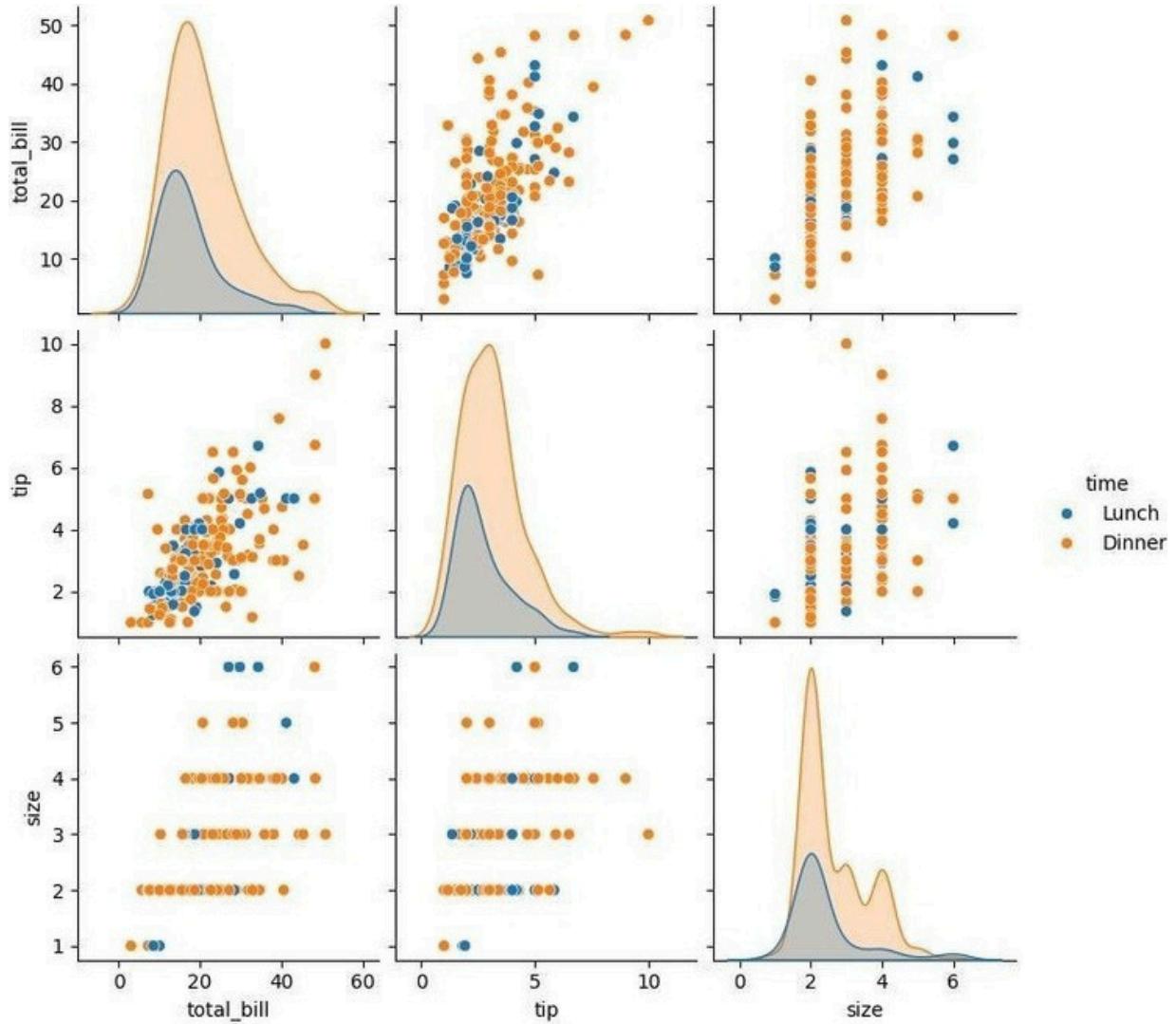
tips.time.value_counts()

time
Dinner      17
r            6
Name: count, dtype: int64

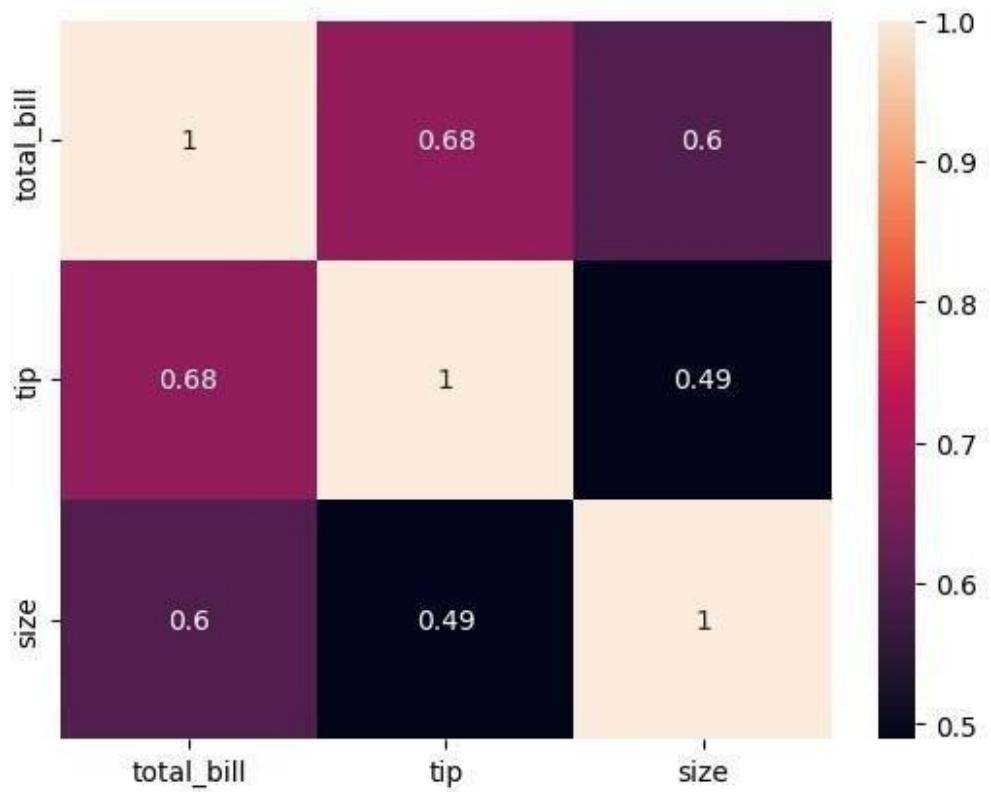
sns.pairplot(tips,hue='time')

<seaborn.axisgrid.PairGrid at 0x20d7cc27990>

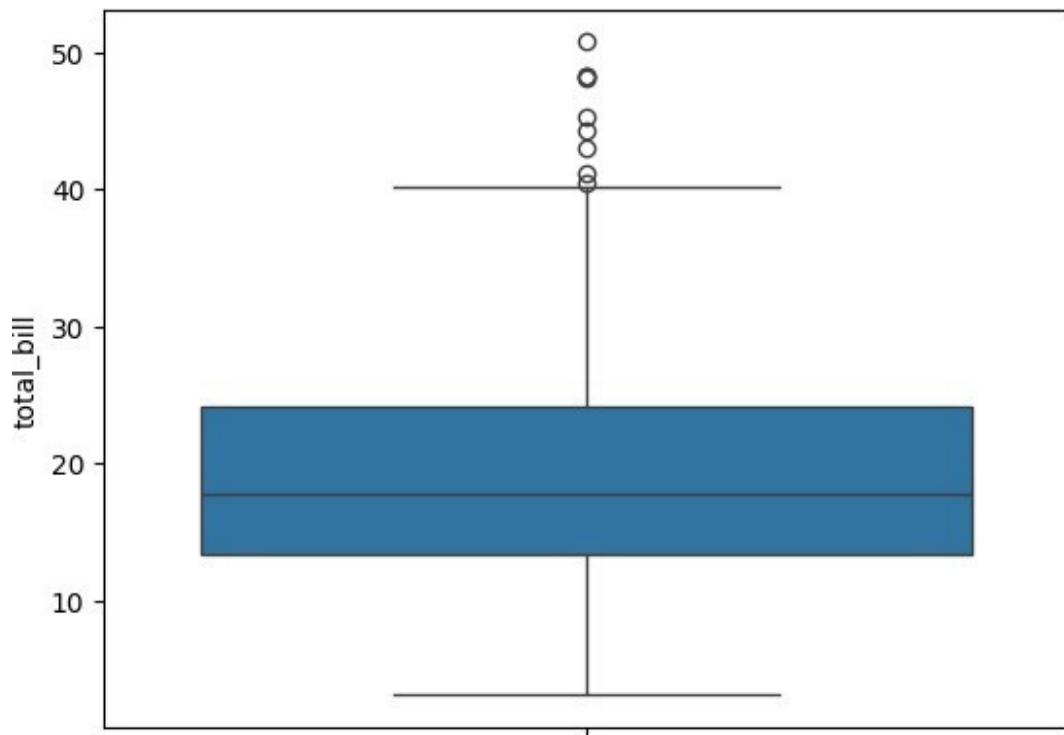
```



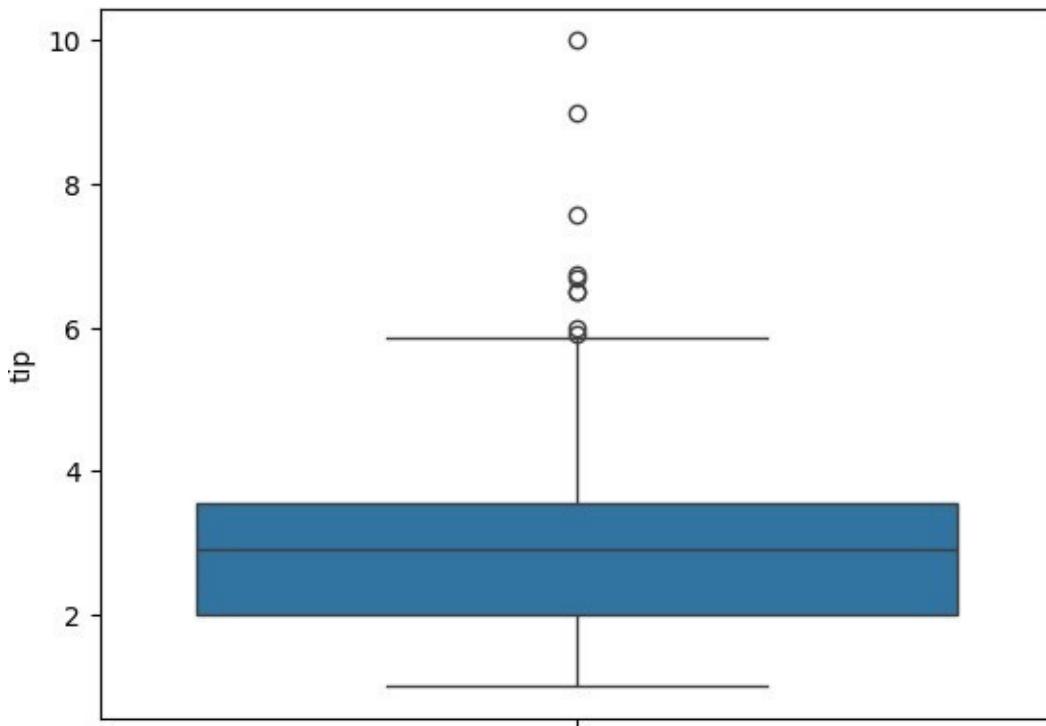
```
sns.heatmap(tips.corr(numeric_only=True), annot=True)  
<Axes: >
```



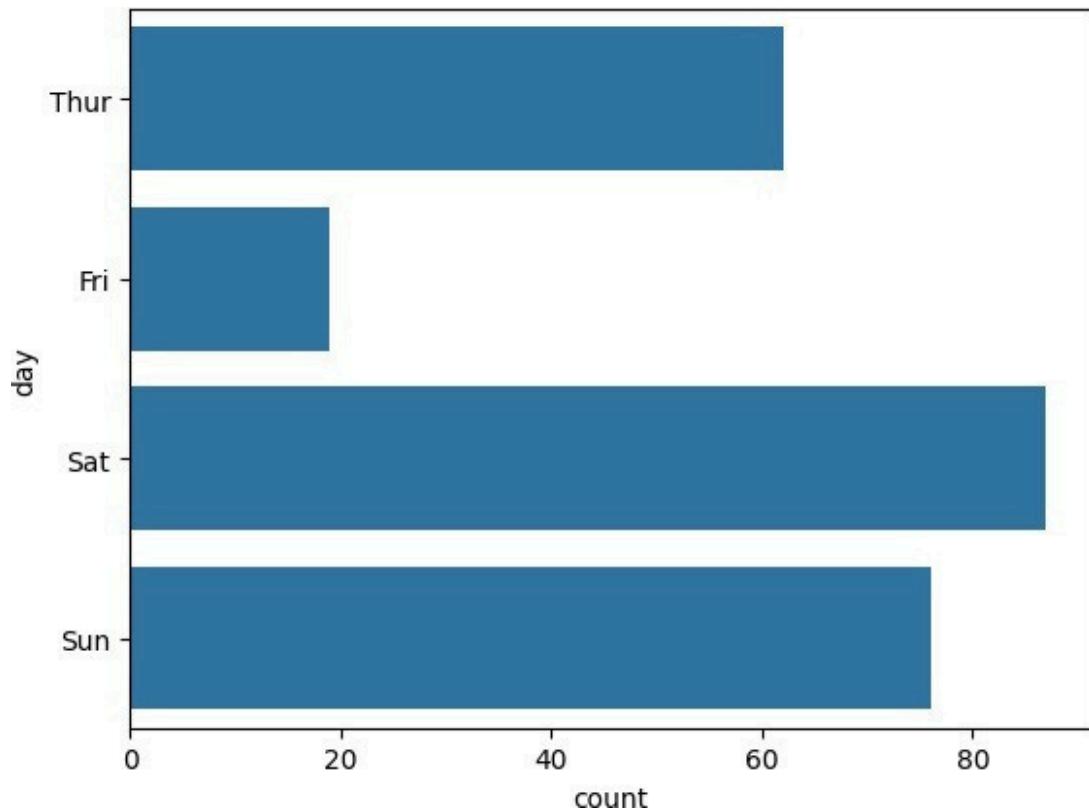
```
sns.boxplot(tips.total_bill)
<Axes: ylabel='total_bill'>
```



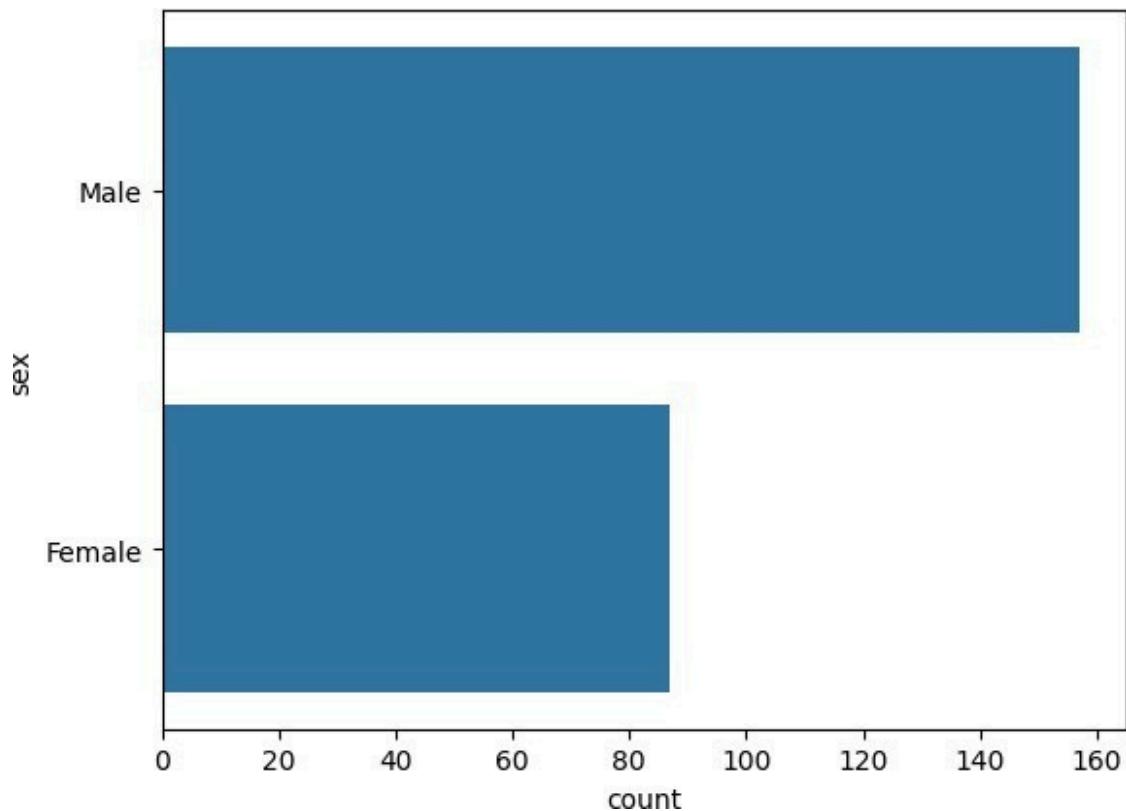
```
sns.boxplot(tips.tip)  
<Axes: ylabel='tip'>
```



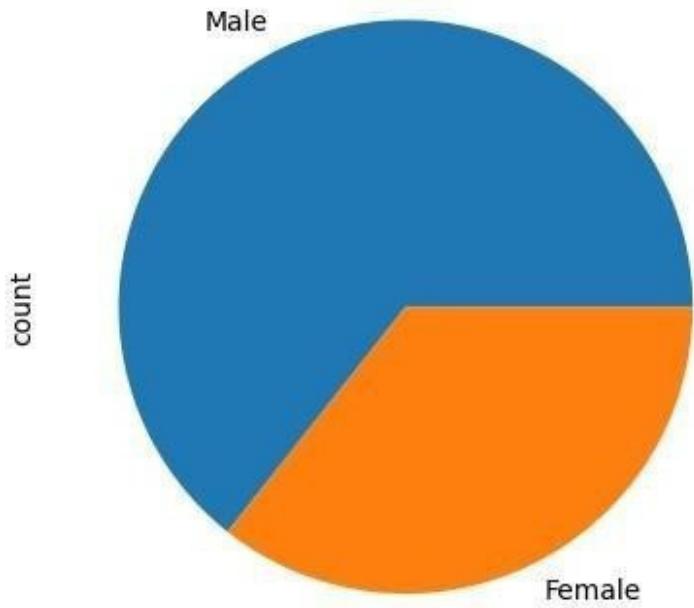
```
sns.countplot(tips.day)
<Axes: xlabel='count', ylabel='day'>
```



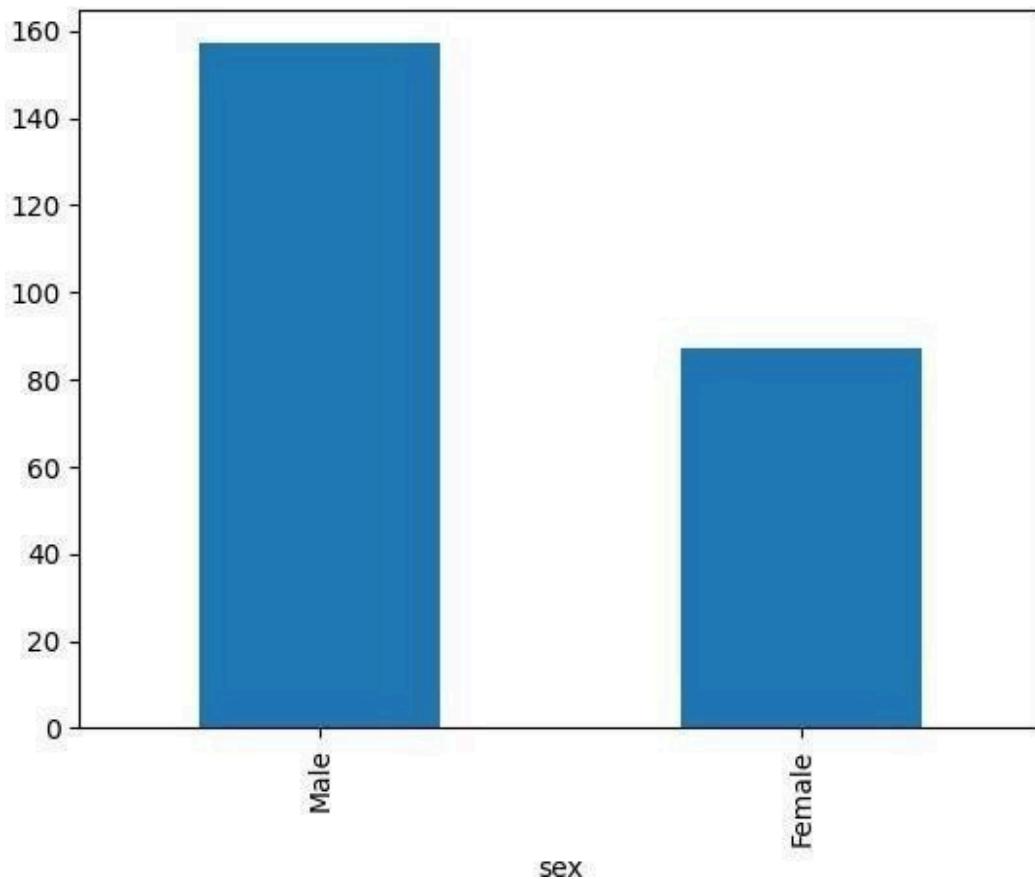
```
sns.countplot(tips.sex)
<Axes: xlabel='count', ylabel='sex'>
```



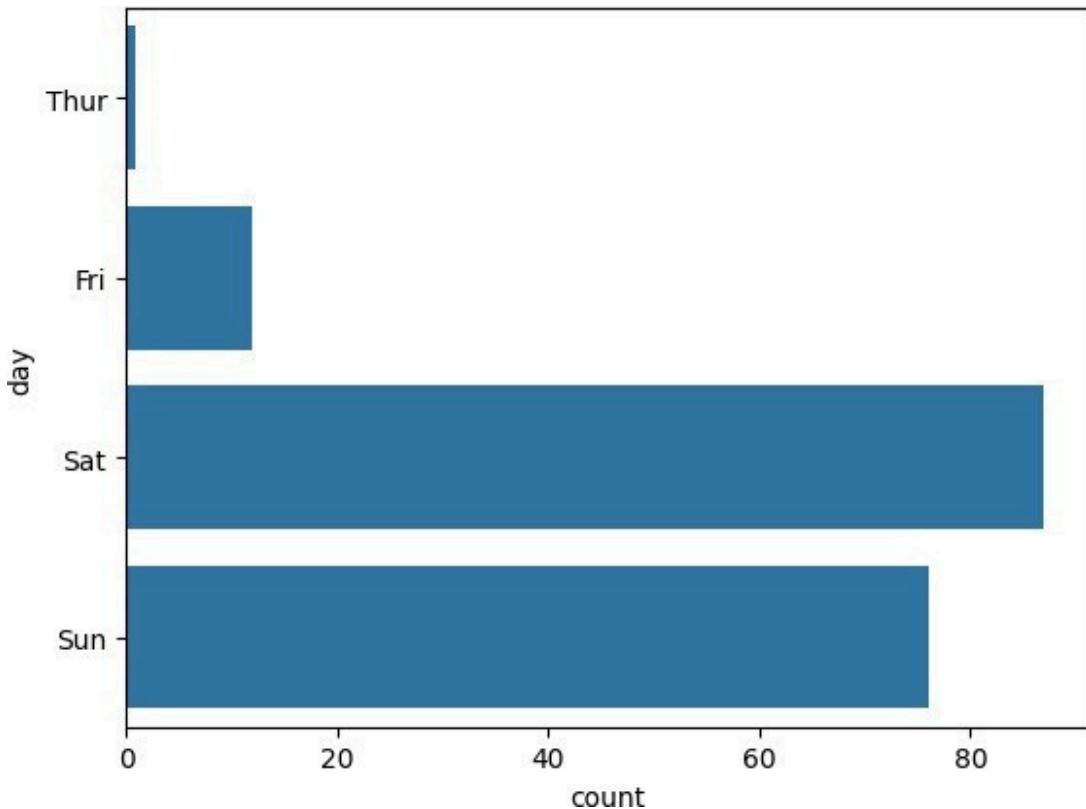
```
tips.sex.value_counts().plot(kind='bar')  
<Axes: ylabel='count'>
```



```
tips.sex.value_counts().plot(kind='bar')  
<Axes: xlabel='sex'>
```



```
sns.countplot(tips[tips.time=='Dinner']['day'])  
<Axes: xlabel='count', ylabel='day'>
```



```
#EX.NO :6 Random Sampling and Sampling Distribution #DATA :  
10.09.2024  
  
#NAME : GOKULANAND B  
#ROLL NO : 230701093  
#DEPARTMENT : B.E COMPUTER SCIENCE AND ENGINEERING - B  
  
import numpy as np  
import matplotlib.pyplot as plt  
population_mean = 50  
population_std = 10  
population_size = 100000  
population = np.random.normal(population_mean, population_std,  
population_size)  
  
sample_sizes = [30, 50, 100]  
num_samples = 1000  
sample_means = {}  
for size in sample_sizes:  
  
    sample_means[size] = []  
    for _ in range(num_samples):  
        sample = np.random.choice(population, size=size, replace=False)  
        sample_means[size].append(np.mean(sample))
```

```

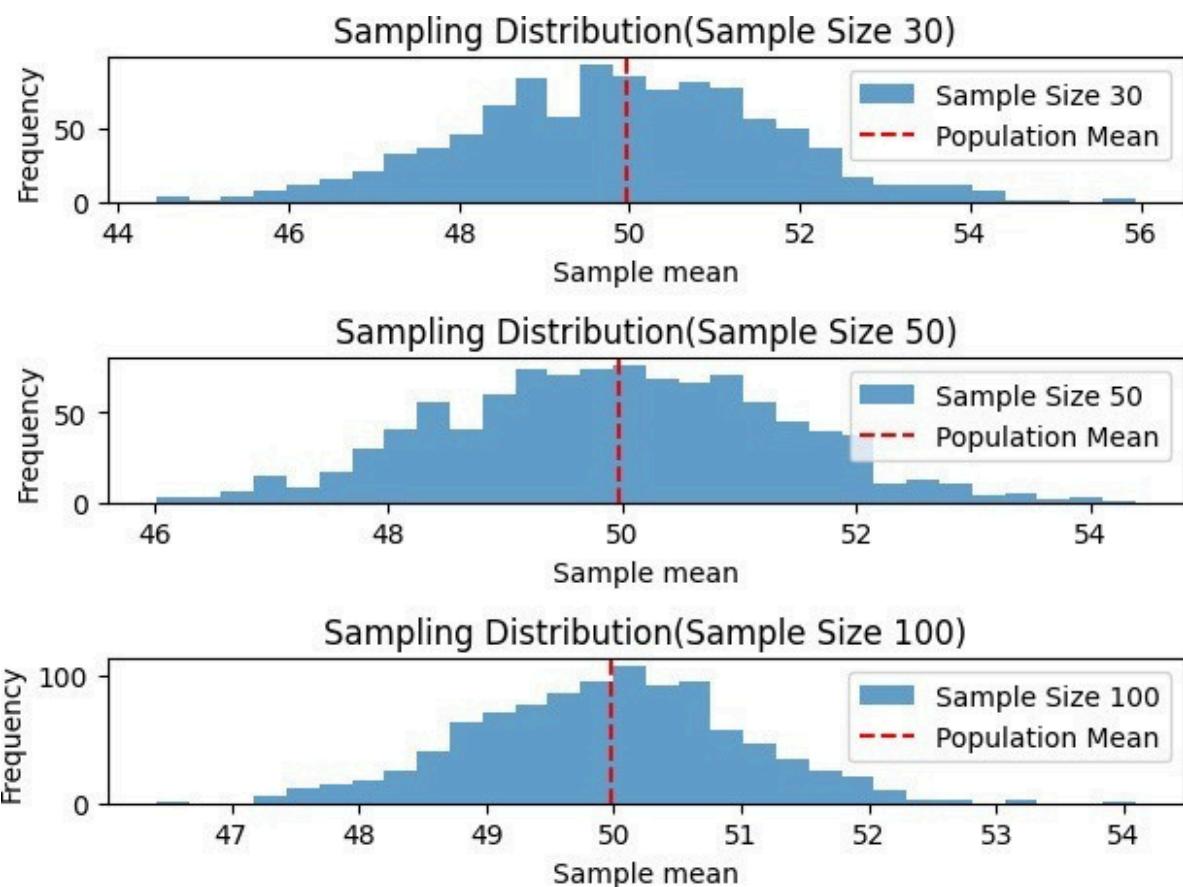
plt.figure(figsize=(12, 8))

<Figure size 1200x800 with 0 Axes>

<Figure size 1200x800 with 0 Axes>

for i, size in enumerate(sample_sizes):
    plt.subplot(len(sample_sizes), 1, i+1)
    plt.hist(sample_means[size], bins=30, alpha=0.7, label=f'Sample Size {size}')
    plt.axvline(np.mean(population), color='red', linestyle= 'dashed',
    linewidth=1.5,
    label= 'Population Mean')
    plt.title(f'Sampling Distribution(Sample Size {size})')
    plt.xlabel('Sample mean')
    plt.ylabel('Frequency') plt.legend()
    plt.tight_layout()
plt.show()

```



```

#EX.NO : 7 Z-Test
#DATA : 10.09.2024

```

```

#NAME : GOKULANAND B
#ROLL NO : 230701093
#DEPARTMENT : B.E COMPUTER SCIENCE AND ENGINEERING - B

import numpy as np
import scipy.stats as stats
sample_data = np.array([152, 148, 151, 149, 147, 153, 150, 148, 152,
149, 151, 150, 149, 152, 151, 148, 150, 152, 149, 150, 148, 153, 151,
150, 149, 152, 148, 151, 150, 153])

population_mean = 150
sample_mean = np.mean(sample_data)
sample_std = np.std(sample_data, ddof=1)

n = len(sample_data)
z_statistic = (sample_mean - population_mean) / (sample_std /
np.sqrt(n))
p_value = 2 * (1 - stats.norm.cdf(np.abs(z_statistic)))

# Assuming sample_mean, z_statistic, and p_value have already been
calculated:
print(f"Sample
{sample_mean:.2f}\n")                                Mean:
print(f"Z-Statistic:
{z_statistic:.4f}\n")                               print(f"P-Value:
{p_value:.4f}\n")

# Significance level
alpha = 0.05
# Decision based on p-value
if p_value < alpha:

    print("Reject the null hypothesis: The average weight is
significantly different from 150 grams.")
else:
    print("Fail to reject the null hypothesis: There is no significant
difference in average weight from 150 grams.")

Sample Mean: 150.20
Z-Statistic: 0.6406
P-Value: 0.5218 Fail to reject the null hypothesis: There is no
significant difference
in average weight from 150 grams.

#EX.NO :8 T-Test
#DATA : 08.10.2024
#NAME : GOKULANAND B

```

```

#ROLL NO : 230701093 #DEPARTMENT : B.E COMPUTER SCIENCE AND
ENGINEERING - B

import numpy as np
import scipy.stats as
stats np.random.seed(42)
sample_size = 25
sample_data = np.random.normal(loc=102, scale=15, size=sample_size)

population_mean = 100
sample_mean = np.mean(sample_data)
sample_std = np.std(sample_data, ddof=1)

n = len(sample_data)
t_statistic, p_value = stats.ttest_1samp(sample_data,population_mean)
# Assuming sample_mean, t_statistic, and p_value have already been
calculated:
print(f"Sample Mean: {sample_mean:.2f}\n")
print(f"T-Statistic: {t_statistic:.4f}\n")
print(f"P-Value: {p_value:.4f}\n")

# Significance level
alpha = 0.05
# Decision based on p-value
if p_value < alpha:

```

print("Reject the null hypothesis: The average IQ score is significantly different from 100.")
else:
 print("Fail to reject the null hypothesis: There is no significant difference in average IQ score from 100.")

Sample Mean: 99.55

T-Statistic: -0.1577 P-Value: 0.8760 Fail to reject the null hypothesis:

There is no significant difference in average IQ score from 100.

#EX.NO :9 Anova TEST

#DATA : 08.10.2024

#NAME : GOKULANAND B

#ROLL NO : 230701093

#DEPARTMENT : B.E COMPUTER SCIENCE AND ENGINEERING - B

```

import numpy as np
import scipy.stats as stats

```

```

from statsmodels.stats.multicomp import pairwise_tukeyhsd

np.random.seed(42)
n_plants = 25
growth_A = np.random.normal(loc=10, scale=2, size=n_plants)
growth_B = np.random.normal(loc=12, scale=3, size=n_plants)
growth_C = np.random.normal(loc=15, scale=2.5, size=n_plants)
all_data = np.concatenate([growth_A, growth_B, growth_C])

treatment_labels = ['A'] * n_plants + ['B'] * n_plants + ['C'] *
n_plants
f_statistic, p_value = stats.f_oneway(growth_A, growth_B, growth_C)

mean_A
np.mean(growth_A) mean_B
= np.mean(growth_B)
mean_C =
np.mean(growth_C)
print(f"Treatment A Mean Growth: {mean_A:.4f}")
print(f"Treatment B Mean Growth: {mean_B:.4f}")
print(f"Treatment C Mean Growth: {mean_C:.4f}")
print(f"F-Statistic: {f_statistic:.4f}")
print(f"P-Value: {p_value:.4f}")

alpha = 0.05
if p_value < alpha:
    print("Reject the null hypothesis: There is significant difference in mean growth rates among the three treatments.") else:
    print("Fail to reject the null hypothesis: There is no significant difference in mean growth rates among the three treatments.")

if p_value < alpha:
    tukey_results = pairwise_tukeyhsd(all_data, treatment_labels,
alpha=0.05)

    print("\nTukey's HSD Post-hoc Test:")
    print(tukey_results)

Treatment A Mean Growth: 9.6730
Treatment B Mean Growth:
11.1377 Treatment C Mean
Growth: 15.2652 F-Statistic:
36.1214
P-Value: 0.0000
Reject the null hypothesis: There is a significant difference in mean growth rates among the three treatments.

Tukey's HSD Post-hoc Test:
Multiple Comparison of Means - Tukey HSD, FWER=0.05

```

```
=====
=
group1 group2 meandiff p-adj      lower upper reject
-----
1.46470.0877 B              -0.16833.0977    False
      A      C   5.5923     0.0 3.95937.2252    True
      B      C   4.1276     0.0 2.49465.7605    True
-----
```

#EX.NO :10 Feature Scaling #DATA : 22.10.2024

#NAME : GOKULANAND B
#ROLL NO : 230701093
#DEPARTMENT : B.E COMPUTER SCIENCE AND
ENGINEERING - B

```
import numpy as np
import pandas as pd
import warnings
warnings.filterwarnings('ignore')
df=pd.read_csv('pre_process_datasample.csv')

df.head()
   Countr   Age   Salary
0      y  44.  72000based      N
1  France   0  48000.0          o
2   Spain  27.0  54000.0        Ye
3  German  30.0  61000.0        s
4      y  38.0      NaN        No
      Spain  40.0          No
df.Country.fillna(df.Country.mode()[0],inplace=True)
) features=df.iloc[:, :-1].values
features
array(['France', 44.0, 72000.0],
['Spain', 27.0, 48000.0],
['Germany', 30.0, 54000.0],
['Spain', 38.0, 61000.0],
['Germany', 40.0, nan],
['France', 35.0, 58000.0],
['Spain', nan, 52000.0],
['France', 48.0, 79000.0],
['Germany', 50.0, 83000.0],
['France', 37.0, 67000.0]],

dtype=object) label=df.iloc[:, -1].values

from sklearn.impute import SimpleImputer
age=SimpleImputer(strategy="mean",missing_values=np.nan)
Salary=SimpleImputer(strategy="mean",missing_values=np.nan)
age.fit(features[:, [1]])
```

```
SimpleImputer()           Salary.fit(features[:,[2]])  
SimpleImputer()   SimpleImputer()   SimpleImputer()  
  
features[:,[1]]=age.transform(features[:,[1]])  
features[:,[2]]=Salary.transform(features[:,[2]])  
features  
  
array(['France', 44.0, 72000.0],  
  
      ['Spain', 27.0, 48000.0],  
      ['Germany', 30.0, 54000.0],  
      ['Spain', 38.0, 61000.0],  
      ['Germany', 40.0, 63777.77777777778],  
      ['France', 35.0, 58000.0],  
      ['Spain', 38.777777777777778, 52000.0],  
      ['France', 48.0, 79000.0],  
      ['Germany', 50.0, 83000.0],  
      ['France', 37.0, 67000.0]), dtype=object)
```

```
from sklearn.preprocessing import OneHotEncoder  
oh = OneHotEncoder(sparse_output=False)  
Country=oh.fit_transform(features[:,[0]])  
Country  
  
array([[1. 0., 0.],  
      ,  
      [0., 0., 1.],  
      [0., 1., 0.],  
      [0., 0., 1.],  
      [0., 1., 0.],  
      [1., 0., 0.],  
      [0., 0., 1.],  
      [1., 0., 0.],  
      [0., 1., 0.],  
      [1., 0., 0.]])
```

```
final_set=np.concatenate((Country,features[:,[1,2]]),axis=1  
) final_set  
  
array([[1.0, 0.0, 0.0, 44.0,  
       72000.0],  
      [0.0, 0.0, 1.0, 27.0, 48000.0],  
      [0.0, 1.0, 0.0, 30.0, 54000.0],  
      [0.0, 0.0, 1.0, 38.0, 61000.0],  
      [0.0, 1.0, 0.0, 40.0, 63777.77777777778],  
      [1.0, 0.0, 0.0, 35.0, 58000.0],  
      [0.0, 0.0, 1.0, 38.777777777777778, 52000.0],
```

```
[1.0, 0.0, 0.0, 48.0, 79000.0], [0.0, 1.0, 0.0, 50.0,  
83000.0], [1.0, 0.0, 0.0, 37.0, 67000.0]], dtype=object)
```

```
from sklearn.preprocessing import StandardScaler
sc=StandardScaler()
sc.fit(final_set)
feat_standard_scaler=sc.transform(final_set)
feat_standard_scaler

array([[ 1.22474487e+00, -6.54653671e-01, -6.54653671e-01,
       7.58874362e-01,  7.49473254e-01],
      [-8.16496581e-01, -6.54653671e-01,  1.52752523e+00,
       -1.71150388e+00,
      [-8.48898881e+00], 1.52752523e+00, -6.54653671e-01,
       -1.27555478e+00,
      [-8.96205882e-01], -6.54653671e-01,  1.52752523e+00,
       -1.13023841e-01,
      [-8.58206688e-01], 1.52752523e+00, -6.54653671e-01,
       1.77608893e-01,  6.63219199e-16],
      [ 1.22474487e+00, -6.54653671e-01,
       -6.554893894e+00],
      [-8.26696882e-01], -6.54653671e-01,  1.52752523e+00,
       0.00000000e+00,
      [ 1.20435688e+00], -6.54653671e-01,
      -6.154603898e+00,  1.38753832e+00],
      [-8.16496581e-01,  1.52752523e+00, -6.54653671e-01,
       1.63077256e+00,  1.75214693e+00],
      [ 1.22474487e+00, -6.54653671e-01,
       -6.54653671e-01,
      -2.58340208e-01, 2.93712492e-01]])
```

```
from sklearn.preprocessing import MinMaxScaler  
mms=MinMaxScaler(feature_range=(0,1))  
mms.fit(final_set)  
feat_minmax_scaler=mms.transform(final_set)  
feat_minmax_scaler
```

```
array([[1.0, 0.0, 0.0, 0.73913043, 0.68571429],  
       [0.0, 0.0, 1.0, 0.0, 0.0],  
       [0.0, 1.0, 0.0, 0.13043478, 0.17142857],  
       [0.0, 0.0, 1.0, 0.47826087, 0.37142857],  
       [0.0, 1.0, 0.0, 0.56521739, 0.45079365],  
       [1.0, 0.0, 0.0, 0.34782609, 0.28571429],  
       [0.0, 0.0, 1.0, 0.51207729, 0.11428571],  
       [1.0, 0.0, 0.0, 0.91304348, 0.88571429],  
       [0.0, 1.0, 0.0, 1.0, 1.0],  
       [1.0, 0.0, 0.0, 0.43478261, 0.54285714]])
```

#EX.NO :11 Linear Regression
#DATA : 29.10.2024

```
#NAME : GOKULANAND B  
#ROLL NO : 230701093  
#DEPARTMENT : B.E COMPUTER SCIENCE AND  
ENGINEERING - B
```

```
import numpy as np  
import pandas as pd  
df = pd.read_csv('Salary_data.csv')  
df
```

```
YearsExperience Salary
```

```
0      1.1    39343  
1      1.3    46205  
2      1.5    37731  
3      2.0    43525  
4      2.2    39891  
5      2.9    56642  
6      3.0    60150  
7      3.2    54445  
8      3.2    64445  
9      3.7    57189  
10     3.9    63218  
11     4.0    55794  
12     4.0    56957  
13     4.1    57081  
14     4.5    61111  
15     4.9    67938  
16     5.1    66029  
17     5.3    83088  
18     5.9    81363  
19     6.0    93940  
20     6.8    91738  
21     7.1    98273  
22     7.9    101302  
23     8.2    113812  
24     8.7    109431  
25     9.0    105582  
26     9.5    116969  
27     9.6    112635  
28    10.3    122391  
29    10.5    121872
```

```
df.info()           <class
```

```
'pandas.core.frame.DataFrame'>
```

```
RangeIndex: 30 entries, 0 to 29
```

```
Data columns (total 2 columns):
```

#	Column	Non-NullCount	Dtyp
-----	-----	-----	e-----

```
0    YearsExperience 30 non-null      float64
1    Salary          30non-null      int64 dtypes: float64(1), int64(1)
memory usage: 612.0 bytes

df.dropna(inplace=True);
df

YearsExperience  Salary
0        1.1   39343
1        1.3   46205
2        1.5   37731
3        2.0   43525
4        2.2   39891
5        2.9   56642
6        3.0   60150
7        3.2   54445
8        3.2   64445
9        3.7   57189
10       3.9   63218
11       4.0   55794
12       4.0   56957
13       4.1   57081
14       4.5   61111
15       4.9   67938
16       5.1   66029
17       5.3   83088
18       5.9   81363
19       6.0   93940
20       6.8   91738
21       7.1   98273
22       7.9  101302
23       8.2  113812
24       8.7  109431
25       9.0  105582
26       9.5  116969
27       9.6  112635
28      10.3  122391
29      10.5  121872

df.info()                         <class
'pandas.core.frame.DataFrame'>
RangeIndex: 30 entries, 0 to 29
Data columns (total 2 columns):
 #   Column           Non-NullCountDtyp
----  --  -----  e  -----
 0   YearsExperience  30non-null      float64
 1   Salary          30non-null      int64
```

```
dtypes: float64(1), int64(1)
memory usage: 612.0 bytes
```

```
df.describe() #descripte statical report
# find out IYER FOR BELOW META DATA
```

	YearsExperience	Salary
count	30.000000	30.000000
mean	5.31333376003.000000	
std	2.837888	27414.429785
min	1.10000037731.000000	
25%	3.20000056720.750000	
50%	4.70000065237.000000	
75%	7.700000100544.750000	
max	10.500000122391.000000	

```
features = df.iloc[:,[0]].values # : - > all row , 0 -> first column
```

```
#iloc index based selection loc location based sentence
```

```
label = df.iloc[:,[1]].values
```

```
features
```

```
array([ 1.1],
      [
        [ 1.3],
        [ 1.5],
        [ 2. ],
        [ 2.2],
        [ 2.9],
        [ 3. ],
        [ 3.2],
        [ 3.2],
        [ 3.2],
        [ 3.7],
        [ 3.9],
        [ 4. ],
        [ 4. ],
        [ 4.1],
        [ 4.1],
        [ 4.5],
        [ 4.5],
        [ 4.9],
        [ 4.9],
        [ 5.1],
        [ 5.1],
        [ 5.3],
        [ 5.9],
        [ 6. ],
        [ 6.8],
        [ 6.8],
        [ 7.1],
        [ 7.9],
        [ 8.2],
        [ 8.7],
        [ 9. ]],
```

```
[ 9.5],  
[ 9.6],  
[10.3],  
[10.5])
```

label

```
array([ 39343]  
     ,  
     [ 46205]  
     [ 37731]  
     ,  
     [ 43525]  
     [ 39891]  
     ,  
     [ 56642]  
     [ 60150]  
     ,  
     [ 54445]  
     ,  
     [ 64445]  
     [ 57189]  
     ,  
     [ 63218]  
     ,  
     [ 55794]  
     ,  
     [ 56957]  
     [ 57081]  
     ,  
     [ 61111]  
     ,  
     [ 67938]  
     ,  
     [ 66029]  
     ,  
     [ 83088]  
     ,  
     [ 81363]  
     ,  
     [ 93940]  
     ,  
     [ 91738]  
     ,  
     [ 98273]  
     ,  
     [101302]  
     ,  
     [113812]  
     ,  
     [109431]  
     ,  
     [105582]
```

```
[116969]  
[112635]  
[122391]  
,  
[121872]], dtype=int64
```

```
from sklearn.model_selection import train_test_split  
x_train,x_test,y_train,y_test =  
train_test_split(features,label,test_size=0.2,random_state=2  
3) # x independent input train 80 % test 20 %  
'''  
y is dependent output  
0.2 allocate test for 20 % automatically train for 80 %  
'''  
\ny is dependent output\n0.2 allocate test for 20 % automatically train  
for 80 %\n'
```

```
from sklearn.linear_model import LinearRegression model =  
LinearRegression() model.fit(x_train,y_train) "" sk - size kit linear  
means using linear regression fit means add data ""  
\n\nsk - size kit \nlinear means using linear regression \nfit  
means add data \n'  
model.score(x_train,y_train)  
"  
accuracy calculating  
96%  
"  
\naccuracy calculating\n96 %\n'  
model.score(x_test,y_test)  
"  
accuracy calculating  
91%  
"  
\naccuracy calculating\n91 %\n' model.coef_ array([[9281.30847068]])  
model.intercept_ array([27166.73682891]) import pickle  
pickle.dump(model,open('SalaryPred.model','wb'))  
  
"  
)  
"  
pickle momory obj to file  
"  
\npickle momory obj to file\n\n'  
model = pickle.load(open('SalaryPred.model','rb'))  
yr_of_exp = float(input("Enter years of exprience: "))  
yr_of_exp_NP = np.array([[yr_of_exp]])  
salary = model.predict(yr_of_exp_NP)  
print("Estimated salary for {} years of exprience is {} .  
.format(yr_of_exp,salary))
```

```
Enter years of expreience: 24
```

```
Estimated salary for 24.0 years of expreience is [[249918.14012525]] .
```

```
print(f" Estimated salary for {yr_of_exp} years of expreience is {salary} . ")
```

```
Estimated salary for 24.0 years of expreience is [[249918.14012525]] .
```

```
#EX.NO:12      LogisticRegression
```

```
#DATA : 05.11.2024
```

```
#NAME : GOKULANAND B
```

```
#ROLL NO : 230701093
```

```
#DEPARTMENT : B.E COMPUTER SCIENCE AND
```

```
ENGINEERING - B
```

```
import numpy as np
```

```
import pandas as pd
```

```
import warnings
```

```
warnings.filterwarnings('ignore')
```

```
df=pd.read_csv("Social_Network_Ads.csv.csv")
```

	User ID	Gender	Age	EstimatedSalary	Purchased
0	15624510	Male	19	19000	0
1	15810944	Male	35	20000	0
2	15668575	Female	26	43000	0
3	15603246	Female	27	57000	0
4	15804002	Male	19	76000	0
..
39515691863	..	Female	46	41000	..
39606071	..	Male	51	23000	1
39715654296	..	Female	50	20000	1
39815755018	..	Male	36	33000	0
39915594041	..	Female	49	36000	1

```
[400 rows x 5 columns]
```

```
df.tail(20)
```

	User ID	Gender	Age	EstimatedSalary	Purchased
380	15683758	Male	42	64000	0
381	15670615	Male	48	33000	1
382	15715622	Female	44	139000	1
383	15707634	Male	49	28000	1
384	15806901	Female	57	33000	1
385	15775335	Male	56	60000	1
386	15724150	Female	49	39000	1
387	15627220	Male	39	71000	0

```

388 15672330 Male 4 3400 1
389 15668521 Female 7 0 1
390 15807837 Mal 4 3500 1
391 15592570 e 8 0 1
392 15748589 Female 4 3300 1
393 15635893 Male 8 0 1
394 15757632 Female 4 2300 0
395 15691863 Female 7 0 1
396 15706071 Male 4 4500 1
397 15654296 Female 5 0 1
398 15755018 Male 6 4200 0
399 15594041 Female 0 0 1
df.head(25)
User ID Gender Age EstimatedSalary Purchased
0 15624510 Male 19 51 19000 0 2300
1 15810944 Male 35 5 20000 0 0
2 15668575 Female 26 0 43000 0 2000
3 15603246 Female 27 3 57000 0 0
4 15804002 Male 19 6 76000 0 3300
5 15728773 Male 27 4 58000 0 0
6 15598044 Female 27 9 84000 0 3600
7 15694829 Female 32 150000 0 0
8 15600575 Male 25 33000 0 0
9 15727311 Female 35 65000 0 0
10 15570769 Female 26 80000 0 0
11 15606274 Female 26 52000 0 0
12 15746139 Male 20 86000 0 0
13 15704987 Male 32 18000 0 0
14 15628972 Male 18 82000 0 0
15 15697686 Male 29 80000 0 0
16 15733883 Male 47 25000 1 0
17 15617482 Male 45 26000 1 0
18 15704583 Male 46 28000 1 0
19 15621083 Female 48 29000 1 0
20 15649487 Male 45 22000 1 0
21 15736760 Female 47 49000 1 0
22 15714658 Male 48 41000 1 0
23 15599081 Female 45 22000 1 0
24 15705113 Male 46 23000 1 0
features =
df.iloc[:,[2,3]].values label =
df.iloc[:,4].values features
array([
    [19, 19000],
    [35, 20000]
])

```

```
[ 26 43000]  
[ , 57000]
```

27

```
[ 19, 76000]  
[ 27, ,  
[ 27, 58000]  
[ , 84000]  
[ ,  
[ 32, 150000]  
[ 25, 33000]  
[ 35, ,  
[ 26, 65000]  
[ 26, ,  
[ 26, 80000]  
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[ 32, ,  
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[ 47, 22000]  
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[ 47, 49000]  
[ , 41000]  
[ , 22000]  
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[ , 20000]  
[ , 28000]  
[ , 30000]
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[ 74000]
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[ 21, 16000]
[ 28, 44000]
[ 27,
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[ 30, 28000]
[ 26,
[ 27, 49000]
[ 27,
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[ 30, 15000]
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[ 54000]
[ 30, 135000]
[ 31, 89000]
[ 24,
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[ 35, 23000]
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[ 32, 18000]
[ 34, 112000]
[ 18, 52000]
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[ 28,
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[ 30, 17000]
[ , 80000]
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[ 29, 28000]
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[ 35, 44000]
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[ 28, 123000]
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[ 27, 37000]
[ 28, 88000]
[       59000]
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[ 35, 68000]
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[ 34, 59000]
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[ 41, 45000]
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[ 36, 76000]
[ 40, 50000]
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[ 46, 47000]
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[      75000]
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[ 32, 135000]
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```

```
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[ 46, 79000]
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```

```
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[ 37, 77000]  
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[ 48, 119000]
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[ 40, , 65000]
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[53, 72000]
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[ 39, 77000]
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```
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[ 47, 71000]
[ 48, 34000]
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[ 46, ,
[ 51, 45000]
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[ 42000]
[ 59000]
[ 41000]
[ 23000]
```

,


```
0,
0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0
0,
0, 0, 0, 0, 1, 0, 1, 0, 1, 0, 1, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0
1,
0, 1, 1, 1, 0, 0, 1, 1, 0, 1, 1, 0, 1, 1, 0, 0, 0, 1, 1
0,
1, 1, 0, 1, 0, 1, 0, 1, 0, 0, 1, 1, 0, 1, 0, 0, 1, 1, 0, 1, 1
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1, 1, 0, 0, 1, 0, 0, 1, 1, 1, 1, 0, 1, 1, 1, 1, 0, 1, 1, 0
1,
0, 1, 0, 1, 1, 1, 1, 0, 0, 0, 1, 1, 0, 1, 1, 1, 1, 0, 0, 0
1,
1, 0, 0, 1, 0, 1, 0, 1, 1, 0, 1, 1, 0, 1, 1, 0, 0, 0, 1
1,
0, 1, 0, 0, 1, 0, 1, 0, 0, 1, 1, 0, 0, 1, 1, 0, 1, 1, 0, 0, 1
1,
1, 0, 1, 1, 1, 0, 1, 0, 1, 1, 1, 0, 1, 1, 1, 1, 0, 1, 1, 1, 0
0,
0, 1, 0, 0, 1, 1, 0, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 0
1,
```

```
1,
1, 1, 0, 1], dtype=int64)
```

```
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
# Assuming `features` and `label` are already defined
```

```
for i in range(1, 401):
```

```
x_train, x_test, y_train, y_test = train_test_split(features,
label, test_size=0.2, random_state=i)
model = LogisticRegression()
model.fit(x_train, y_train)

train_score = model.score(x_train, y_train)
test_score = model.score(x_test, y_test)

if test_score > train_score:
    print(f"Test Score: {test_score:.4f} | Train Score:
{train_score:.4f} | Random State: {i}")

"""

Test Score: 0.9000 | Train Score: 0.8406 | Random State: 4
Test Score: 0.8625 | Train Score: 0.8500 | Random State: 5
Test Score: 0.8625 | Train Score: 0.8594 | Random State: 6
Test Score: 0.8875 | Train Score: 0.8375 | Random State: 7
Test Score: 0.8625 | Train Score: 0.8375 | Random State: 9
Test Score: 0.9000 | Train Score: 0.8406 | Random State: 10
Test Score: 0.8625 | Train Score: 0.8562 | Random State: 14
Test Score: 0.8500 | Train Score: 0.8438 | Random State: 15
Test Score: 0.8625 | Train Score: 0.8562 | Random State: 16
Test Score: 0.8750 | Train Score: 0.8344 | Random State: 18
Test Score: 0.8500 | Train Score: 0.8438 | Random State: 19
Test Score: 0.8750 | Train Score: 0.8438 | Random State: 20
Test Score: 0.8625 | Train Score: 0.8344 | Random State: 21
Test Score: 0.8750 | Train Score: 0.8406 | Random State: 22
Test Score: 0.8750 | Train Score: 0.8406 | Random State: 24
Test Score: 0.8500 | Train Score: 0.8344 | Random State: 26
Test Score: 0.8500 | Train Score: 0.8406 | Random State: 27
Test Score: 0.8625 | Train Score: 0.8344 | Random State: 30
Test Score: 0.8625 | Train Score: 0.8562 | Random State: 31
Test Score: 0.8750 | Train Score: 0.8531 | Random State: 32
Test Score: 0.8625 | Train Score: 0.8438 | Random State: 33
Test Score: 0.8750 | Train Score: 0.8313 | Random State: 35
Test Score: 0.8625 | Train Score: 0.8531 | Random State: 36
Test Score: 0.8875 | Train Score: 0.8406 | Random State: 38
Test Score: 0.8750 | Train Score: 0.8375 | Random State: 39
Test Score: 0.8875 | Train Score: 0.8375 | Random State: 42
Test Score: 0.8750 | Train Score: 0.8469 | Random State: 46
Test Score: 0.9125 | Train Score: 0.8313 | Random State: 47
Test Score: 0.8750 | Train Score: 0.8313 | Random State: 51
Test Score: 0.9000 | Train Score: 0.8438 | Random State: 54
Test Score: 0.8500 | Train Score: 0.8438 | Random State: 57
Test Score: 0.8750 | Train Score: 0.8438 | Random State: 58
Test Score: 0.9250 | Train Score: 0.8375 | Random State: 61
```

Test Score: 0.8875 | Train Score: 0.8344 | Random State: 65 Test
Score: 0.8875 | Train Score: 0.8406 | Random State: 68 Test
Score: 0.9000 | Train Score: 0.8313 | Random State: 72 Test
Score: 0.8875 | Train Score: 0.8375 | Random State: 75 Test
Score: 0.9250 | Train Score: 0.8250 | Random State: 76 Test
Score: 0.8625 | Train Score: 0.8406 | Random State: 77 Test
Score: 0.8625 | Train Score: 0.8594 | Random State: 81 Test
Score: 0.8750 | Train Score: 0.8375 | Random State: 82 Test
Score: 0.8875 | Train Score: 0.8375 | Random State: 83 Test
Score: 0.8625 | Train Score: 0.8531 | Random State: 84 Test
Score: 0.8625 | Train Score: 0.8406 | Random State: 85 Test
Score: 0.8625 | Train Score: 0.8406 | Random State: 87 Test
Score: 0.8750 | Train Score: 0.8469 | Random State: 88 Test
Score: 0.9125 | Train Score: 0.8375 | Random State: 90 Test
Score: 0.8625 | Train Score: 0.8500 | Random State: 95 Test
Score: 0.8750 | Train Score: 0.8500 | Random State: 99 Test
Score: 0.8500 | Train Score: 0.8406 | Random State: 101 Test
Score: 0.8500 | Train Score: 0.8406 | Random State: 102 Test
Score: 0.9000 | Train Score: 0.8250 | Random State: 106 Test
Score: 0.8625 | Train Score: 0.8406 | Random State: 107 Test
Score: 0.8500 | Train Score: 0.8344 | Random State: 109 Test
Score: 0.8500 | Train Score: 0.8406 | Random State: 111 Test
Score: 0.9125 | Train Score: 0.8406 | Random State: 112 Test
Score: 0.8625 | Train Score: 0.8500 | Random State: 115 Test
Score: 0.8625 | Train Score: 0.8406 | Random State: 116 Test
Score: 0.8750 | Train Score: 0.8344 | Random State: 119 Test
Score: 0.9125 | Train Score: 0.8281 | Random State: 120 Test
Score: 0.8625 | Train Score: 0.8594 | Random State: 125 Test
Score: 0.8500 | Train Score: 0.8469 | Random State: 128 Test
Score: 0.8750 | Train Score: 0.8500 | Random State: 130 Test
Score: 0.9000 | Train Score: 0.8438 | Random State: 133 Test
Score: 0.9250 | Train Score: 0.8344 | Random State: 134 Test
Score: 0.8625 | Train Score: 0.8500 | Random State: 135 Test
Score: 0.8750 | Train Score: 0.8313 | Random State: 138 Test
Score: 0.8625 | Train Score: 0.8500 | Random State: 141 Test
Score: 0.8500 | Train Score: 0.8469 | Random State: 143 Test
Score: 0.8500 | Train Score: 0.8469 | Random State: 146 Test
Score: 0.8500 | Train Score: 0.8438 | Random State: 147 Test
Score: 0.8625 | Train Score: 0.8500 | Random State: 148 Test
Score: 0.8750 | Train Score: 0.8375 | Random State: 150 Test
Score: 0.8875 | Train Score: 0.8313 | Random State: 151 Test
Score: 0.9250 | Train Score: 0.8438 | Random State: 152 Test
Score: 0.8500 | Train Score: 0.8406 | Random State: 153 Test
Score: 0.9000 | Train Score: 0.8438 | Random State: 154 Test
Score: 0.9000 | Train Score: 0.8406 | Random State: 155 Test
Score: 0.8875 | Train Score: 0.8469 | Random State: 156 Test
Score: 0.8875 | Train Score: 0.8344 | Random State: 158 Test
Score: 0.8750 | Train Score: 0.8281 | Random State: 159 Test
Score: 0.9000 | Train Score: 0.8313 | Random State: 161

Test Score: 0.8500 | Train Score: 0.8375 | Random State: 163
Test Score: 0.8750 | Train Score: 0.8313 | Random State: 164
Test Score: 0.8625 | Train Score: 0.8500 | Random State: 169
Test Score: 0.8750 | Train Score: 0.8406 | Random State: 171
Test Score: 0.8500 | Train Score: 0.8406 | Random State: 172
Test Score: 0.9000 | Train Score: 0.8250 | Random State: 180
Test Score: 0.8500 | Train Score: 0.8344 | Random State: 184
Test Score: 0.9250 | Train Score: 0.8219 | Random State: 186
Test Score: 0.9000 | Train Score: 0.8313 | Random State: 193
Test Score: 0.8625 | Train Score: 0.8500 | Random State: 195
Test Score: 0.8625 | Train Score: 0.8406 | Random State: 196
Test Score: 0.8625 | Train Score: 0.8375 | Random State: 197
Test Score: 0.8750 | Train Score: 0.8406 | Random State: 198
Test Score: 0.8875 | Train Score: 0.8375 | Random State: 199
Test Score: 0.8875 | Train Score: 0.8438 | Random State: 200
Test Score: 0.8625 | Train Score: 0.8375 | Random State: 202
Test Score: 0.8625 | Train Score: 0.8406 | Random State: 203
Test Score: 0.8875 | Train Score: 0.8313 | Random State: 206
Test Score: 0.8625 | Train Score: 0.8344 | Random State: 211
Test Score: 0.8500 | Train Score: 0.8438 | Random State: 212
Test Score: 0.8625 | Train Score: 0.8344 | Random State: 214
Test Score: 0.8750 | Train Score: 0.8313 | Random State: 217
Test Score: 0.9625 | Train Score: 0.8187 | Random State: 220
Test Score: 0.8750 | Train Score: 0.8438 | Random State: 221
Test Score: 0.8500 | Train Score: 0.8406 | Random State: 222
Test Score: 0.9000 | Train Score: 0.8438 | Random State: 223
Test Score: 0.8625 | Train Score: 0.8531 | Random State: 227
Test Score: 0.8625 | Train Score: 0.8344 | Random State: 228
Test Score: 0.9000 | Train Score: 0.8406 | Random State: 229
Test Score: 0.8500 | Train Score: 0.8438 | Random State:

Test Score: 0.8750 | Train Score: 0.8469 | Random State: 232
Test Score: 0.9125 | Train Score: 0.8406 | Random State: 233
Test Score: 0.8625 | Train Score: 0.8406 | Random State: 234
Test Score: 0.8500 | Train Score: 0.8469 | Random State: 235
Test Score: 0.8750 | Train Score: 0.8469 | Random State: 236
Test Score: 0.8875 | Train Score: 0.8500 | Random State: 239
Test Score: 0.8500 | Train Score: 0.8438 | Random State: 241
Test Score: 0.8875 | Train Score: 0.8250 | Random State: 242
Test Score: 0.8750 | Train Score: 0.8469 | Random State: 243
Test Score: 0.8750 | Train Score: 0.8406 | Random State: 244
Test Score: 0.8750 | Train Score: 0.8406 | Random State: 245
Test Score: 0.8750 | Train Score: 0.8469 | Random State: 246
Test Score: 0.8625 | Train Score: 0.8594 | Random State: 247
Test Score: 0.8875 | Train Score: 0.8438 | Random State: 248
Test Score: 0.8625 | Train Score: 0.8500 | Random State: 250
Test Score: 0.8750 | Train Score: 0.8313 | Random State: 251
Test Score: 0.8875 | Train Score: 0.8438 | Random State: 252
Test Score: 0.8625 | Train Score: 0.8469 | Random State: 255
Test Score: 0.9000 | Train Score: 0.8406 | Random State: 257
Test Score: 0.8625 | Train Score: 0.8562 | Random State: 260

Test Score: 0.8625 | Train Score: 0.8406 | Random State: 266
Test Score: 0.8625 | Train Score: 0.8375 | Random State: 268
Test Score: 0.8750 | Train Score: 0.8406 | Random State: 275
Test Score: 0.8625 | Train Score: 0.8500 | Random State: 276
Test Score: 0.9250 | Train Score: 0.8375 | Random State: 277
Test Score: 0.8750 | Train Score: 0.8469 | Random State: 282
Test Score: 0.8500 | Train Score: 0.8469 | Random State: 283
Test Score: 0.8500 | Train Score: 0.8438 | Random State: 285
Test Score: 0.9125 | Train Score: 0.8344 | Random State: 286
Test Score: 0.8500 | Train Score: 0.8406 | Random State: 290
Test Score: 0.8500 | Train Score: 0.8406 | Random State: 291
Test Score: 0.8500 | Train Score: 0.8469 | Random State: 292
Test Score: 0.8625 | Train Score: 0.8375 | Random State: 294
Test Score: 0.8875 | Train Score: 0.8281 | Random State: 297
Test Score: 0.8625 | Train Score: 0.8344 | Random State: 300
Test Score: 0.8625 | Train Score: 0.8500 | Random State: 301
Test Score: 0.8875 | Train Score: 0.8500 | Random State: 302
Test Score: 0.8750 | Train Score: 0.8469 | Random State: 303
Test Score: 0.8625 | Train Score: 0.8344 | Random State: 305
Test Score: 0.9125 | Train Score: 0.8375 | Random State: 306
Test Score: 0.8750 | Train Score: 0.8469 | Random State: 308
Test Score: 0.9000 | Train Score: 0.8438 | Random State: 311
Test Score: 0.8625 | Train Score: 0.8344 | Random State: 313
Test Score: 0.9125 | Train Score: 0.8344 | Random State: 314
Test Score: 0.8750 | Train Score: 0.8375 | Random State: 315
Test Score: 0.9000 | Train Score: 0.8469 | Random State: 317
Test Score: 0.9125 | Train Score: 0.8219 | Random State: 319
Test Score: 0.8625 | Train Score: 0.8500 | Random State: 321
Test Score: 0.9125 | Train Score: 0.8281 | Random State: 322
Test Score: 0.8500 | Train Score: 0.8469 | Random State:

328
Test Score: 0.8500 | Train Score: 0.8375 | Random State:
332
Test Score: 0.8875 | Train Score: 0.8531 | Random State:
336
Test Score: 0.8500 | Train Score: 0.8375 | Random State:
337
Test Score: 0.8750 | Train Score: 0.8406 | Random State:
343
Test Score: 0.8625 | Train Score: 0.8438 | Random State:
346
Test Score: 0.8875 | Train Score: 0.8313 | Random State:
351
Test Score: 0.8625 | Train Score: 0.8500 | Random State:
352
Test Score: 0.9500 | Train Score: 0.8187 | Random State:
354
Test Score: 0.8625 | Train Score: 0.8500 | Random State:
356
Test Score: 0.9125 | Train Score: 0.8406 | Random State:
357
Test Score: 0.8625 | Train Score: 0.8375 | Random State:
358
Test Score: 0.8500 | Train Score: 0.8406 | Random State:
362
Test Score: 0.9000 | Train Score: 0.8438 | Random State:
363
Test Score: 0.8625 | Train Score: 0.8531 | Random State:
364
Test Score: 0.9375 | Train Score: 0.8219 | Random State:
366
Test Score: 0.9125 | Train Score: 0.8406 | Random State:
369
Test Score: 0.8625 | Train Score: 0.8531 | Random State:
371
Test Score: 0.9250 | Train Score: 0.8344 | Random State:
376
Test Score: 0.9125 | Train Score: 0.8281 | Random State:
377

```

Test Score: 0.8875 | Train Score: 0.8500 | Random State: 378
Test Score: 0.8875 | Train Score: 0.8500 | Random State: 379
Test Score: 0.8625 | Train Score: 0.8406 | Random State: 382
Test Score: 0.8625 | Train Score: 0.8594 | Random State: 386
Test Score: 0.8500 | Train Score: 0.8375 | Random State: 387
Test Score: 0.8750 | Train Score: 0.8281 | Random State: 388
Test Score: 0.8500 | Train Score: 0.8438 | Random State: 394
Test Score: 0.8625 | Train Score: 0.8375 | Random State: 395
Test Score: 0.9000 | Train Score: 0.8438 | Random State: 397
Test Score: 0.8625 | Train Score: 0.8438 | Random State: 400
el,test_size=10)

LogisticRegression()

print(finalModel.score(x_train,y_train))
)
print(finalModel.score(x_train,y_train))
)

0.85
0.85

from sklearn.metrics import classification_report
print(classification_report(label,finalModel.predict(features)))

precision    recall   f1-score support

```

0	0.8	0.91	0.8	25
1	6	0.73	9	7
	0.83		0.77	143
accuracy			0.85	40
macro avg	0.8	0.8	0.83	0
weighted avg	0.85	0.8	0.85	40
		5		0
				40
				0

